Physics Based Image Deshadowing Using Local Linear Model

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A. Supplementary Material

A.1. Shadow masks estimation fine-tuning

In figure 1, we present an example for the shadow mask estimation before and after fine-tuning the BDRAR network on the ISTD+ dataset. Similar to the results reported in the main text for the ISTD+ dataset, in this example the IoU increased from 0.06 to 0.95 and the BER dropped from 11.4 to 0.75 after the fine-tuning.

Shadow Image After fine-tuning Before fine-tuning

Figure 1. Comparing predicted shadow mask before and after fine-tuning.

A.2. Network architecture

Table 1 summarizes the parameters of the convolutional layers in our network. The network contains convolutions with a growing dilation rate which allows the network to process information from a large receptive field (513×513), while using a small number of parameters.

A.3. Estimated shadow coefficients maps

We show an example for our network estimated shadow coefficients maps w and b for a single color channel (red) in figure 2. As can be seen, the coefficients maps are piecewise smooth and the values of w and b depend on the pixel's color and spatial location. For example, higher values of w can be found at the upper shadow part close to the occluding figure, where the shadow intensity is greater.

A.4. Qualitative results

In figures 3 and 4, we provide qualitative results for the SRD dataset and additional results for the ISTD+ dataset and compare our method with several other state-of-the-art methods.

Layer	Convolution	Dilation	Receptive Field
1	3×3	1	3×3
2	3×3	2	7×7
3	3×3	4	15×15
4	3×3	8	31×31
5	3×3	16	63×63
6	3×3	32	127×127
7	3×3	64	255×255
8	3×3	128	511×511
9	3×3	1	513×513
10	1×1	1	513×513

Table 1. Our shadow removal network

References

[1] Xiaodong Cun, Chi-Man Pun, and Cheng Shi. Towards ghost-free shadow removal via dual hierarchical aggregation network and shadow matting gan. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pages 10680–10687, 2020. 2

[2] Xiaowei Hu, Chi-Wing Fu, Lei Zhu, Jing Qin, and Pheng-Ann Heng. Direction-aware spatial context features for shadow detection and removal. *IEEE transactions on pattern analysis and machine intelligence*, 42(11):2795–2808, 2019. 2, 3

[3] Hieu Le and Dimitris Samaras. Shadow removal via shadow image decomposition. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 8578–8587, 2019. 3

[4] Hieu Le and Dimitris Samaras. From shadow segmentation to shadow removal. In *European Conference on Computer Vision*, pages 264–281. Springer, 2020. 3

[5] Zhihao Liu, Hui Yin, Xinyi Wu, Zhenyao Wu, Yang Mi, and Song Wang. From shadow generation to shadow removal. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 4927–4936, 2021. 3

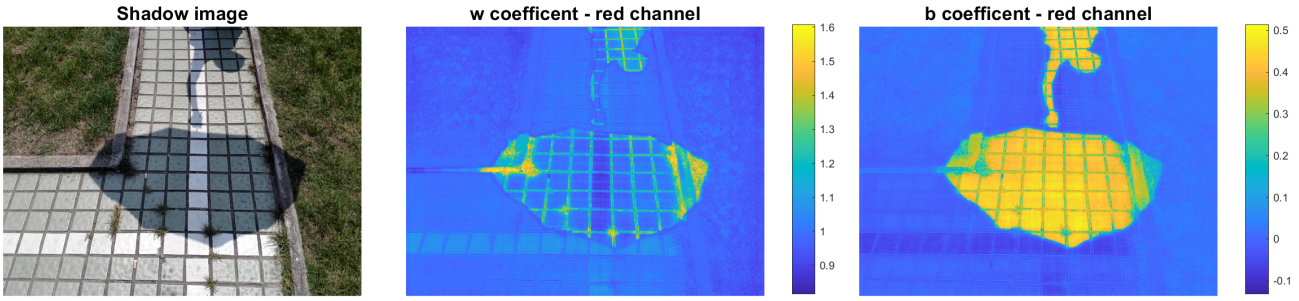
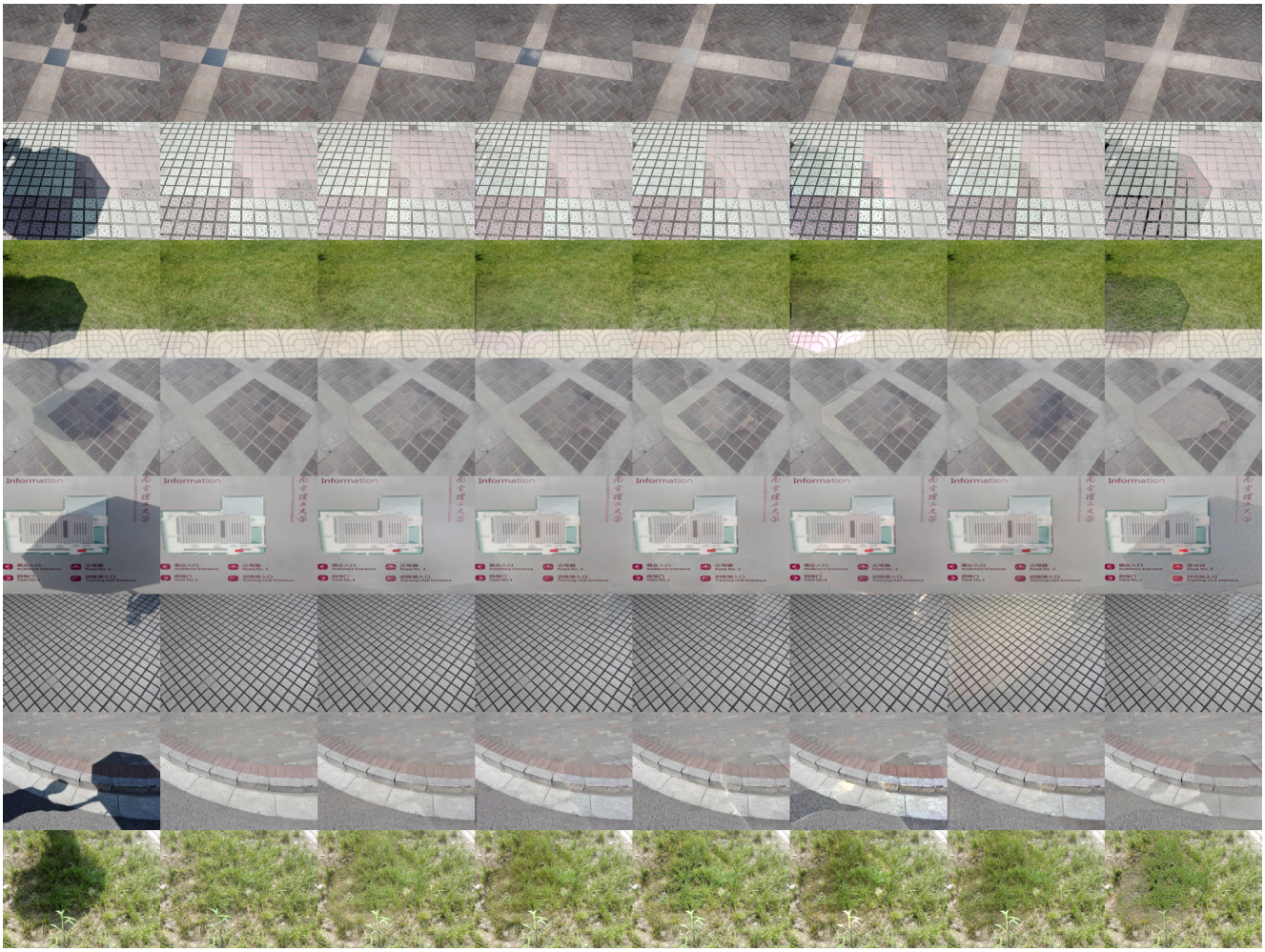


Figure 2. Estimated shadow coefficients maps w and b for the red channel.

Shadow | Shadow Free | Ours | Hu *et al*. [2] | Cun *et al*. [1]

Figure 3. **SRD qualitative results.**



Shadow | Shadow Free | Ours | Le *et al.* [3] | Liu *et al.* *Sup* [5] | Le *et al.* [4] | Hu *et al.* [2] | Liu *et al.* [5]

Figure 4. **ISTD+ qualitative results.**