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Depth-Aware Shadow Removal
Supplementary Material

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In this supplementary material, we provide more experiments to demonstrate the efficiency of the proposed method.

1. Shadow removal evaluation on ISTD+ dataset

The adjusted ISTD dataset (ISTD+) [LS19] has the same number of triplets as ISTD [WLY18]. The ISTD+ adjusts the color inconsistent between the shadow images and the shadow-free images of the ISTD dataset.

Figure 1 shows visual comparison results of shadow removal on the ISTD+ dataset between the proposed method and other state-of-the-art methods, including G2R-ShadowNet [LYW*21], Auto-Exposure [FZG*21], and DC-ShadowNet [JST21]. From Figure 1, we can see that the results of the methods G2R-ShadowNet [LYW*21], Auto-Exposure [FZG*21], and DC-ShadowNet [JST21] introduce some artifacts after shadow removal. However, the proposed method can generate more fidelity shadow removal results in the shadow regions.

Table 1 shows the quantitative results of the proposed method and several state-of-the-art shadow removal methods on the ISTD+ dataset. We use the RMSE metrics to evaluate the performance of the shadow removal method in the shadow region, non-shadow region, and the whole image. From Table 1, we can see that the proposed method achieves the best performance than the other method in the shadow regions and the whole image. However, the shadow and shadow-free image pairs are captured at different times, which results in slightly color inconsistency in the ISTD dataset. The RMSE between the shadow image and the non-shadow image in the non-shadow area is 12.9 according to [LS19]. To mitigate the color inconsistency, the ISTD+ dataset transforms the pixel values in the non-shadow region of each shadow-free image to map into their counterpart values in the shadow image to reduce the RMSE between the shadow-free image and the shadow image in the non-shadow region. Therefore, all shadow removal methods can achieve satisfactory results in non-shadow regions. The proposed method is not trained on the ISTD+ dataset, but we obtain the best performance in the shadow regions, which demonstrates the effectiveness and generalization of the proposed method.

Table 1: Shadow removal results of our networks compared to state-of-the-art shadow removal methods on the ISTD+ dataset (RMSE)

Method	Shadow	Non-shadow	All
ST-CGAN [WLY18]	13.4	7.7	8.7
DeshadowNet [QTH*17]	15.9	6.0	7.6
Mask-ShadowGAN [HJFH19]	12.4	4.0	5.3
Auto-Exposure [FZG*21]	<u>6.5</u>	<u>3.8</u>	<u>4.2</u>
DC-ShadowNet	10.3	**3.5**	4.6
Our	**5.1**	<u>3.8</u>	**4.1**

2. The number of models parameters

Table 2 reports the number of parameters of each model in the proposed method.

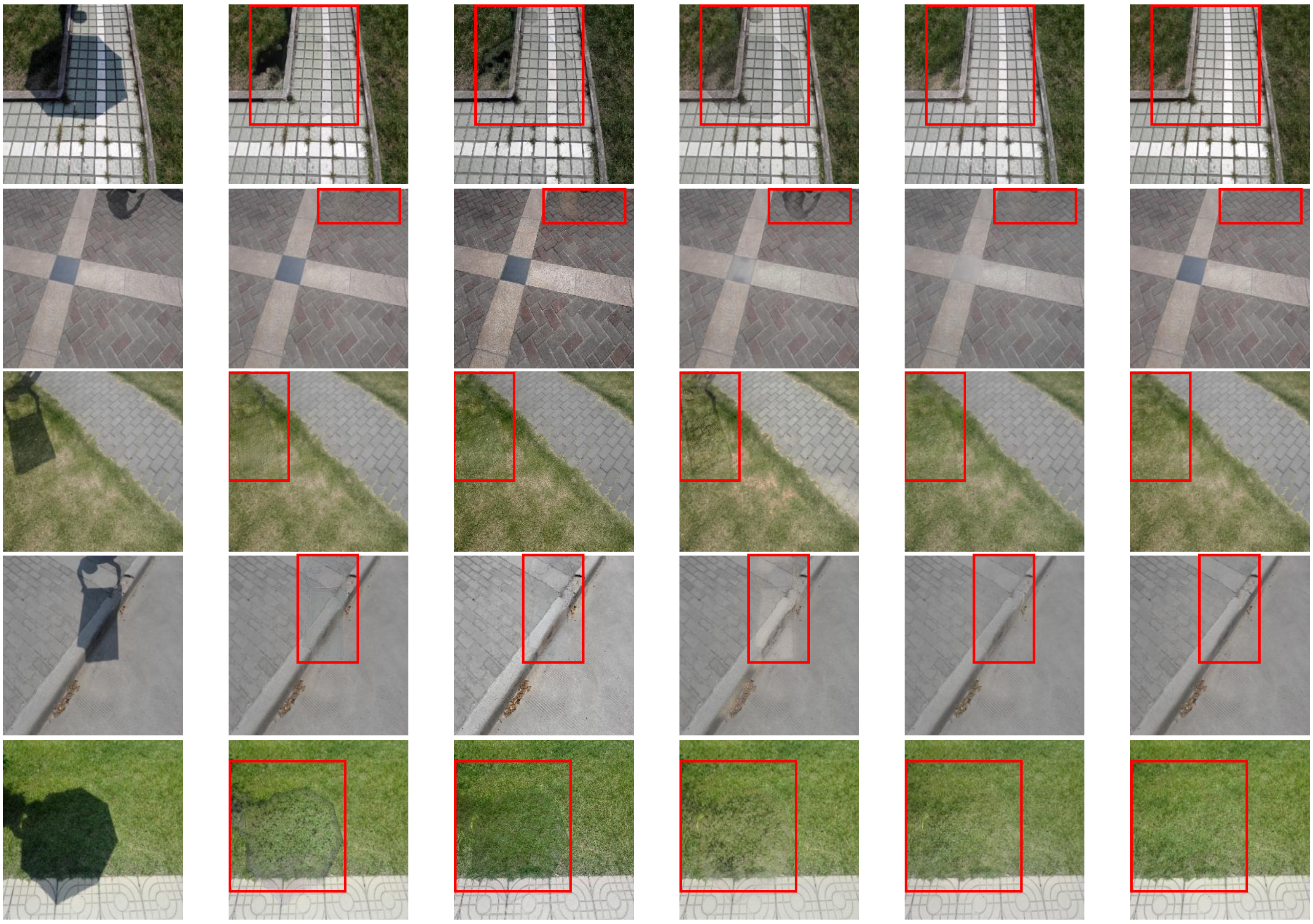
Table 2: The number of models parameters

Model	Params (M)
shadow removal	184.88
boundary refinement	579.54
depth predition	482.86
all	1247.28

In Table 3, we compare the number of parameters with several state-of-the-art shadow removal methods.

Table 3: Comparison of our model parameters with other model parameters

Method	Params (M)
G2R-ShadowNet [HJFH19]	211.1
Auto-Fusion [FZG*21]	524.3
DC-ShadowNet [JST21]	1318.1
Ours	1247.2



(a) (b) (c) (d) (e) (f)

Figure 1: Visual comparison results of shadow removal on ISTD+ dataset. (a) Shadow images. (b) G2R-ShadowNet [HJFH19]. (c) Auto-Exposure [FZG*21]. (d) DC-ShadowNet [JST21]. (e) Ours. (f) Ground Truth.

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