Towards Ghost-free Shadow Removal via Dual Hierarchical Aggregation Network and Shadow Matting GAN (Supplementary Material)

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Architectures

generator We extract the features of VGG19 from the pre-trained model on ImageNet of (CONV1_2 (64), CONV2_2 (128), CONV3_2 (256), CONV4_2 (512) and CONV5_2 (512)) layers as the multi-scale features. Adding input, we have 1475 different features maps. The first convolution of our network uses a 1×1 convolution to squeeze the features to 64 feature channels. Then, we use the k-Dilated Convolution-ReLU-BatchNormaltion block with a growth dilation k ($k = 1, 2, 4, 8, 16, 32, 64$). These dilated convolution extract the low-level features more carefully than global feature. In each Spatial Polling Pyramid (SPP), we use 4 average pooling layer with different pooling rate to produce the fine-level features in multi scale, and we resize the features to the full size using bilinear interpolation. We refine the final output from the concatenation of these features together with the original. In each Aggregation Node, we use the default reduction rate (16) in each linear layer of squeeze-and-excitation block.

Discriminator architectures We use the similar discriminator as our shadow synthesis network. Each discriminator is builded with 5 convolution layers with ReLU non-linear activation and Batch Normalization layer.

Hyper-parameters λ In multi-layer perceptual loss, we use the same hyper-parameters as previous. In detail, as in the Equation.(3) in the main paper: k from $0..6$ have a $lambda_k$ equal to $1, 1/2.6, 1/4.8, 1/3.7, 1/5.6, 1 * 10/1.5$ respectively.

More Results

Shadow Removal on ISTD As shown in Figure. 1 and Figure. 2, we plot more results of our methods compared with the state-of-the-art learning-based methods and hand-craft feature-based methods on shadow removal/detection on ISTD dataset. It is obviously that our method gain better results than others with a larger margin.

Shadow Synthesis We plot some shadow images which is created by our shadow image synthesis algorithm in Figure. 3. We compare our method with pix2pix and Masked-ShadowGAN, which only consider shadow synthesis as the cycle-consistence. As shown in Figure, our method show better results both in detail and image quality.

Shadow Detection on SBU As shown in Figure. 4, we plot more results of our methods compared with the state-of-the-art learning-based methods and hand-craft feature-based methods on shadow removal/detection on SBU dataset. It is obviously that our method gain better results than others with a larger margin.

Shadow Removal on SRD As shown in Figure. 5 and Figure. 6, we plot more results of our methods compared with the state-of-the-art learning-based methods on the shadow removal results. It is obviously that our method gain better results than others with a larger margin.

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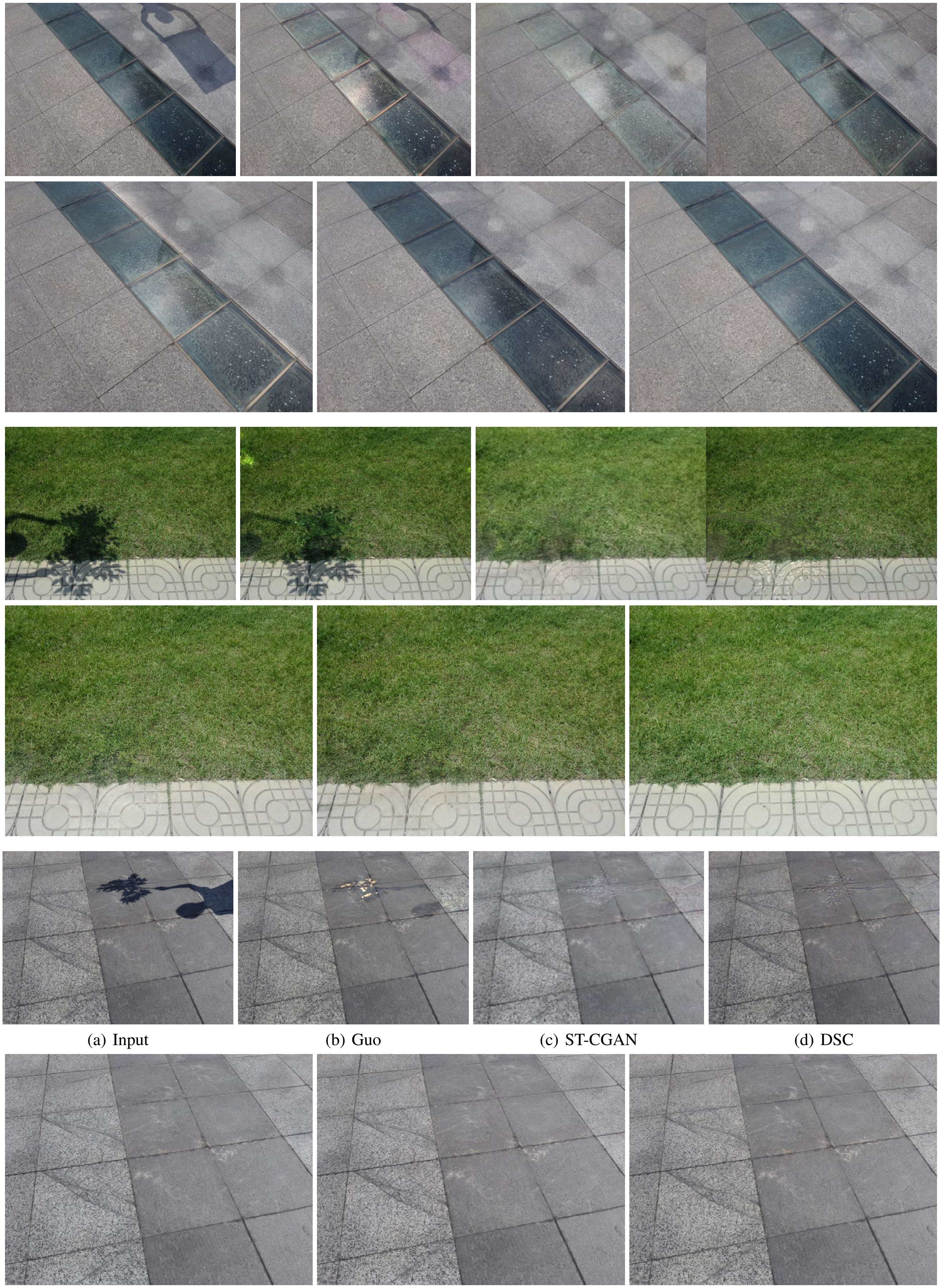
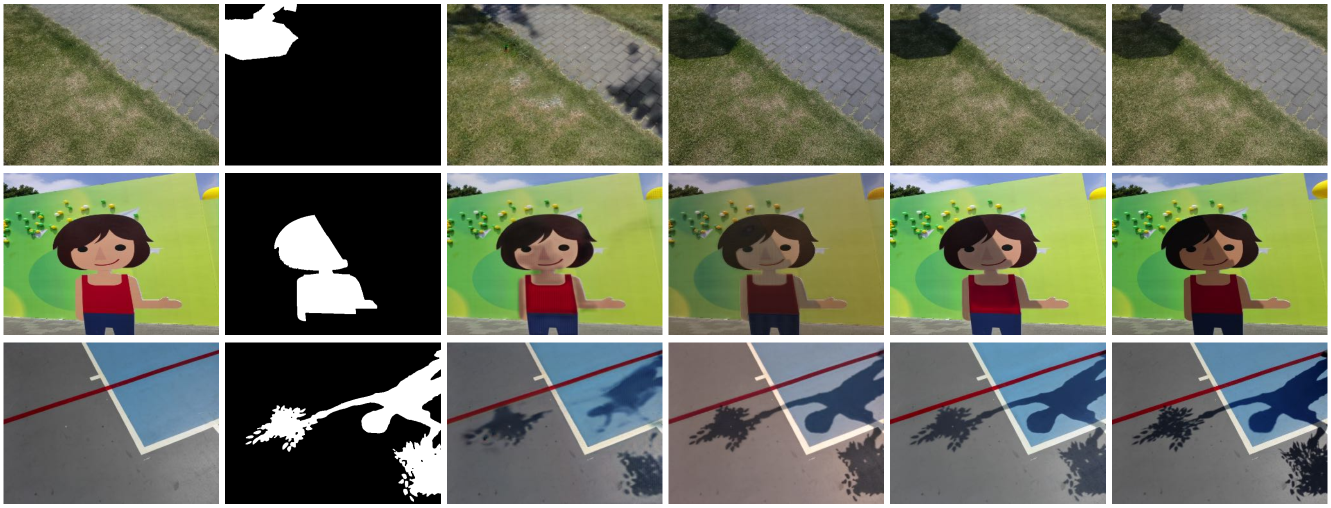


Figure 1: More shadow removal results on ISTD dataset.

(a) Input (b) Guo (c) ST-CGAN (d) DSC

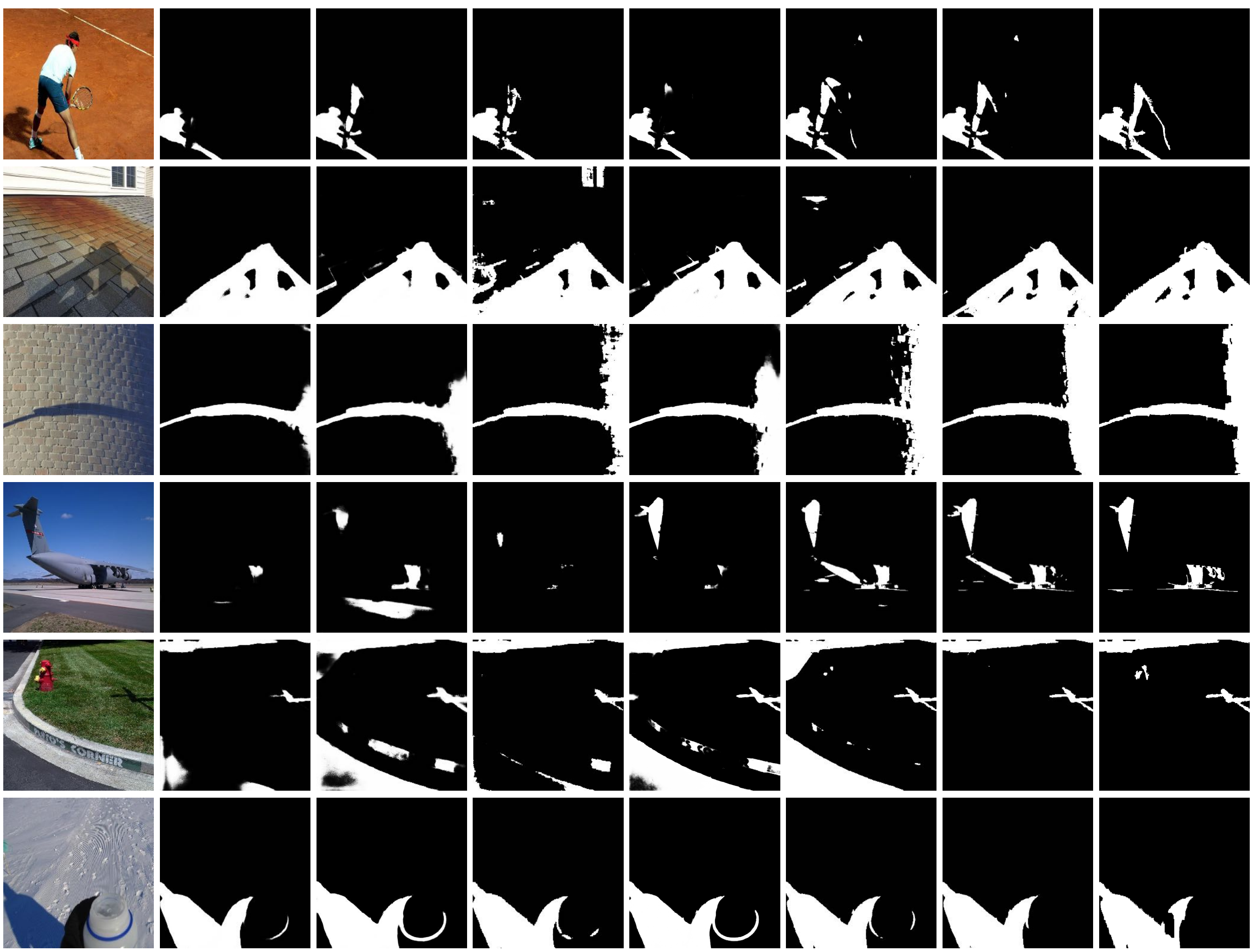
(e) Ours (f) Ours+DA (g) Target

Figure 2: More shadow removal results on ISTD dataset.



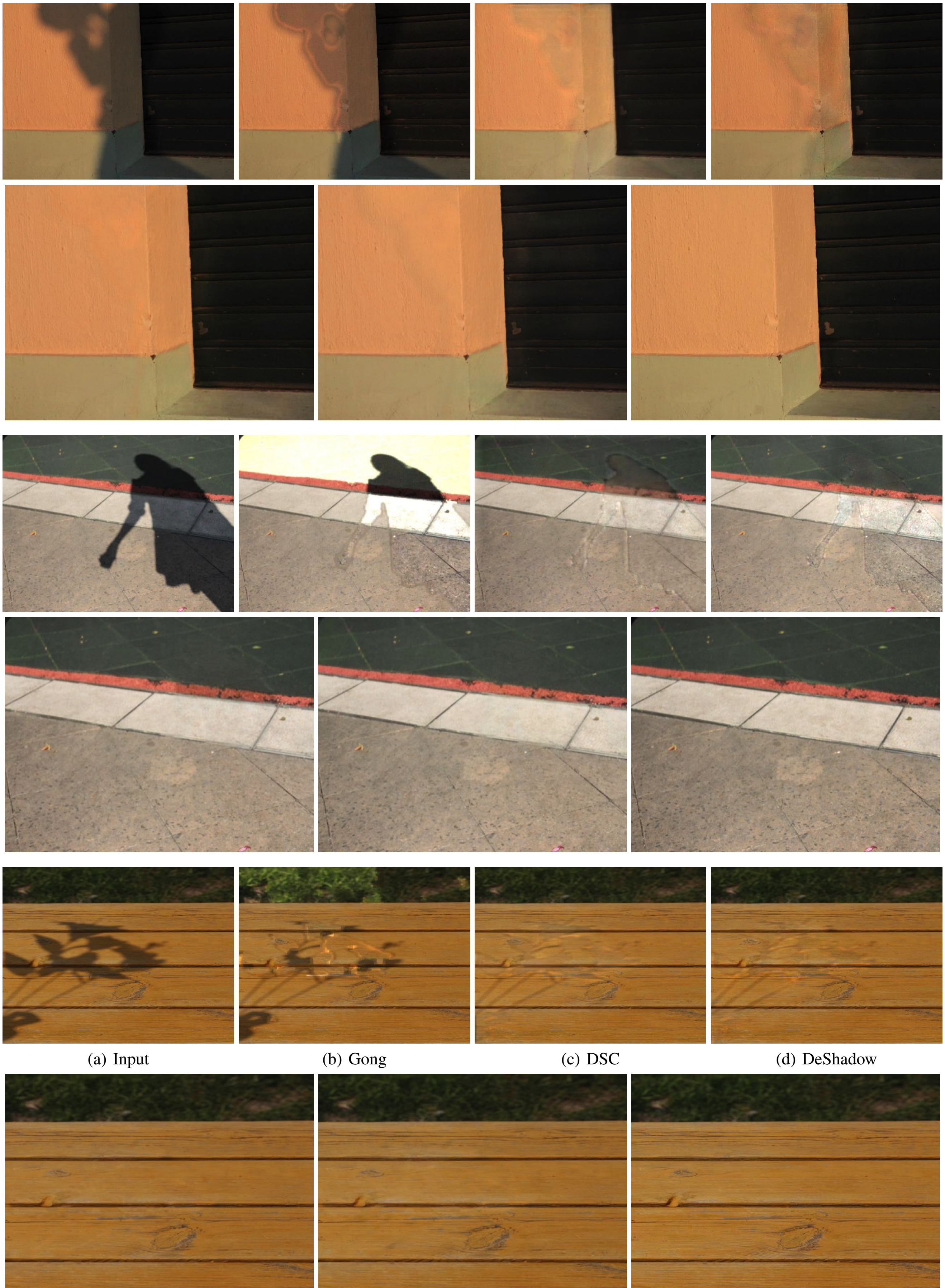
(a) Input (b) Mask (c) Mask-GAN (d) pix2pix (e) Ours (f) Target

Figure 3: Comparison on quality of shadow synthesis.



(f) input (g) DSC (h) BDRAR (i) ADNet (j) DSD (k) Ours (l) Ours+ (m) Target

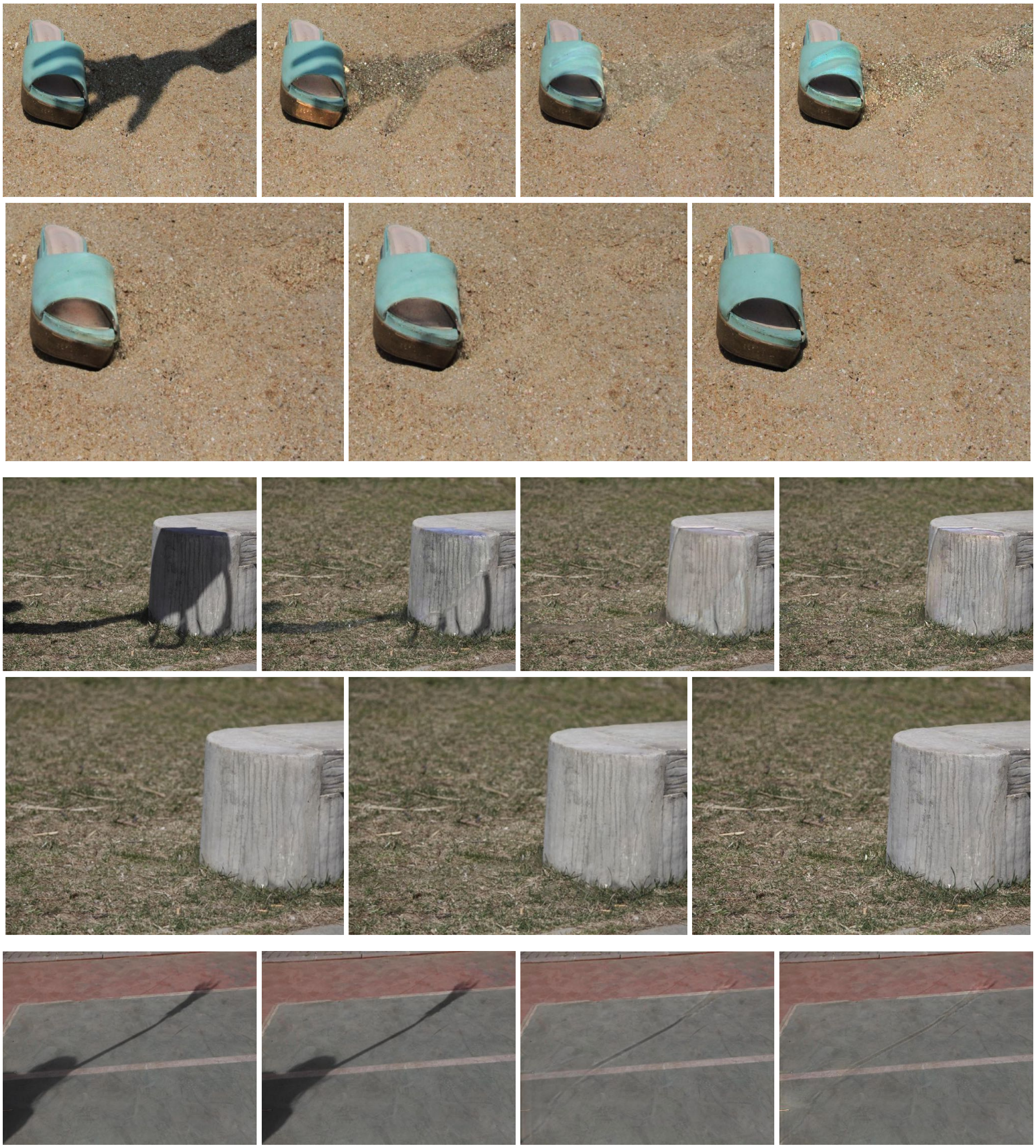
Figure 4: More Shadow detection results on SBU dataset.



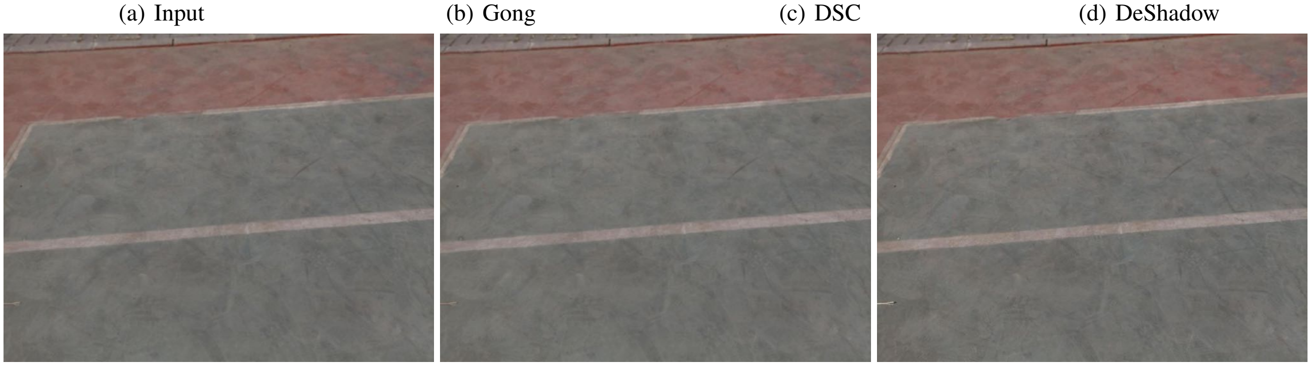
(a) Input (b) Gong (c) DSC (d) DeShadow

(e) Ours (f) Ours+DA (g) Target

Figure 5: More shadow removal results on SRD dataset.



(a) Input (b) Gong (c) DSC (d) DeShadow



(e) Ours (f) Ours+DA (g) Target

Figure 6: More shadow removal results on SRD dataset.