

Supplementary for “HighlightRemover: Spatially Valid Pixel Learning for Image Specular Highlight Removal”

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ABSTRACT

The supplementary material provides more discussions and visualization comparisons to support the main paper.

1 DATASET ANALYSIS

To comprehensively understand our dataset, we perform a series of statistical analyses.

Highlight areas. We use the highlight mask manually annotated by using Photoshop to measure the proportion of highlight regions for each image. Figure 1(a) presents the statistics for the ratio of highlight regions in the image.

Color contrast. Highlights in real-world images are usually high-intensity and texture-less, which means that the color contrast between highlight and non-highlight areas is usually high. We use the X^2 distance to measure the color contrast between highlight and non-highlight areas in the highlight image. Figure 1(b) plots the color contrast of the images in our dataset, where a higher horizontal axis means a higher contrast. We can see that the contrast of highlights in the images is relatively uniform and includes highlights of various intensity types.

Highlight location distribution. To analyze the spatial distribution of highlights, we use a probabilistic image to show the main spatial distribution of highlights in the dataset, as shown in Figure 1(c). We can observe that the highlights are mainly concentrated in the center and lower position of the image. The highlights observed by the human visual imaging system also focus on these regions.

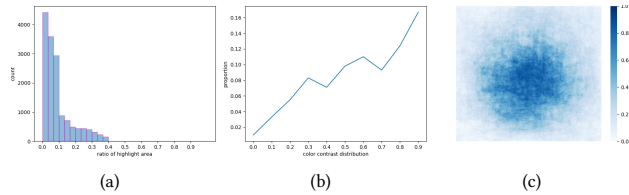


Figure 1: Statistics of dataset analysis. (a) is the statistics for the ratio of highlight areas in the images. (b) is statistics of color contrast, and (c) is statistics of highlight location distribution.

Material categories. Our NSH dataset contains various reflective and smooth materials that can easily produce highlights under light sources in daily life, such as plastic, rubber, stone, porcelain, leather, wax, plants, etc. We take images from different combinations of angles and shapes to increase the variety and complexity of the dataset.

2 DISCUSSION AND EXPERIMENTS

Figure 2 presents some other specular highlight removal results for real-world natural images captured by smartphones or downloaded from the internet. From these results, we can observe that,

our method effectively removes highlights in the image, and the recovered illumination and textures in highlight regions are consistent with surrounding environment. Although we focus on highlights removal, our HighlightRNet also can detect the highlight regions based on the predicted removal result. Figure 2 also gives the promising highlight detection results for the images, which effectively distinguish the specular highlight regions.

Figure 3, Figure 4 and Figure 7 provide some visual specular highlight removal results to further demonstrate the superiority of our method. Compared with these methods, our HighlightRNet can effectively remove specular highlights in the images, and our results are closer to the ground-truth images.

Figure 5 presents some other highlight removal results, containing some challenging cases, such as overexposure, heavy texture, uniform patterns and white surfaces in the highlight regions. Apparently, results recovered by our method look more natural and have little artifacts. Our superior results illustrate the robustness and generalization ability of the proposed method.

More recently, Fu *et al.* [2] propose a three-stage framework for specular highlight removal. Before producing the highlight removal results, this method needs to decompose the input image into its albedo and shading components firstly. They train the network using five labeled data for supervision, such as albedo image, shading image, specular residue map, highlight-free image and tone correction image. Such treatment may causes the error accumulation and reduces the performance of the following highlight removal due to image decomposition is also a difficult task. In contrast, our method only requires highlight-free images for supervision. Besides, we use SSHR dataset used by Fu *et al.* [2] to train our method. Figure 7 concludes the comparison results. From the results, we can observe that, our method achieves the better values than that of Fu *et al.* [2], clearly demonstrating the effectiveness of our HighlightRNet.

REFERENCES

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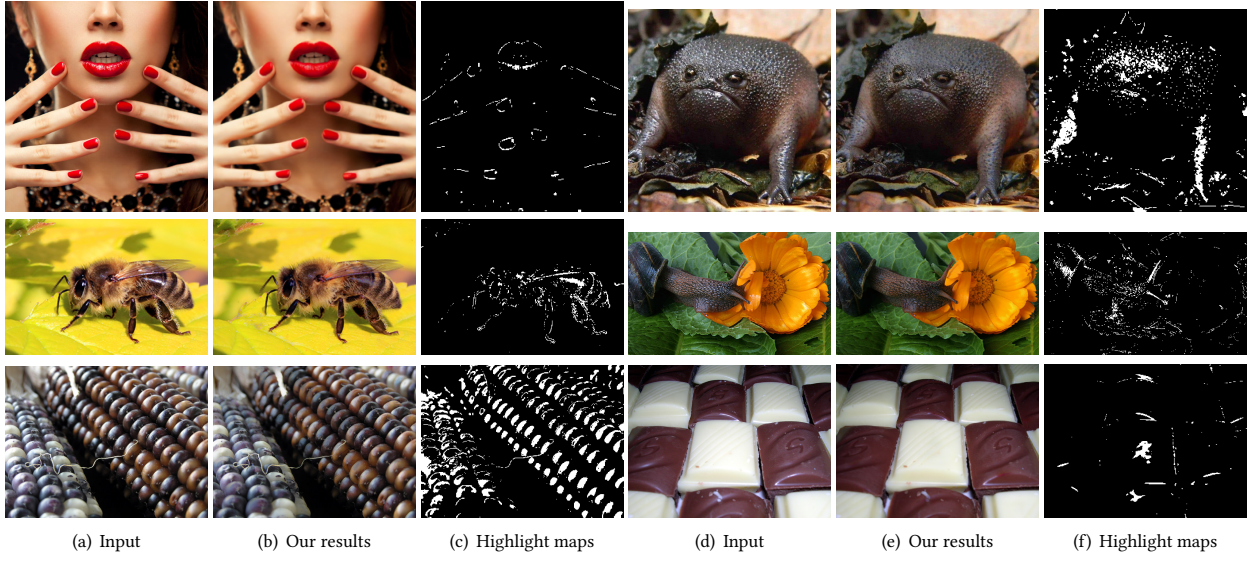


Figure 2: Highlight removal and detection results for real-world natural images. Probability map is the specular highlight detection result, and the white regions indicate the highlight areas.

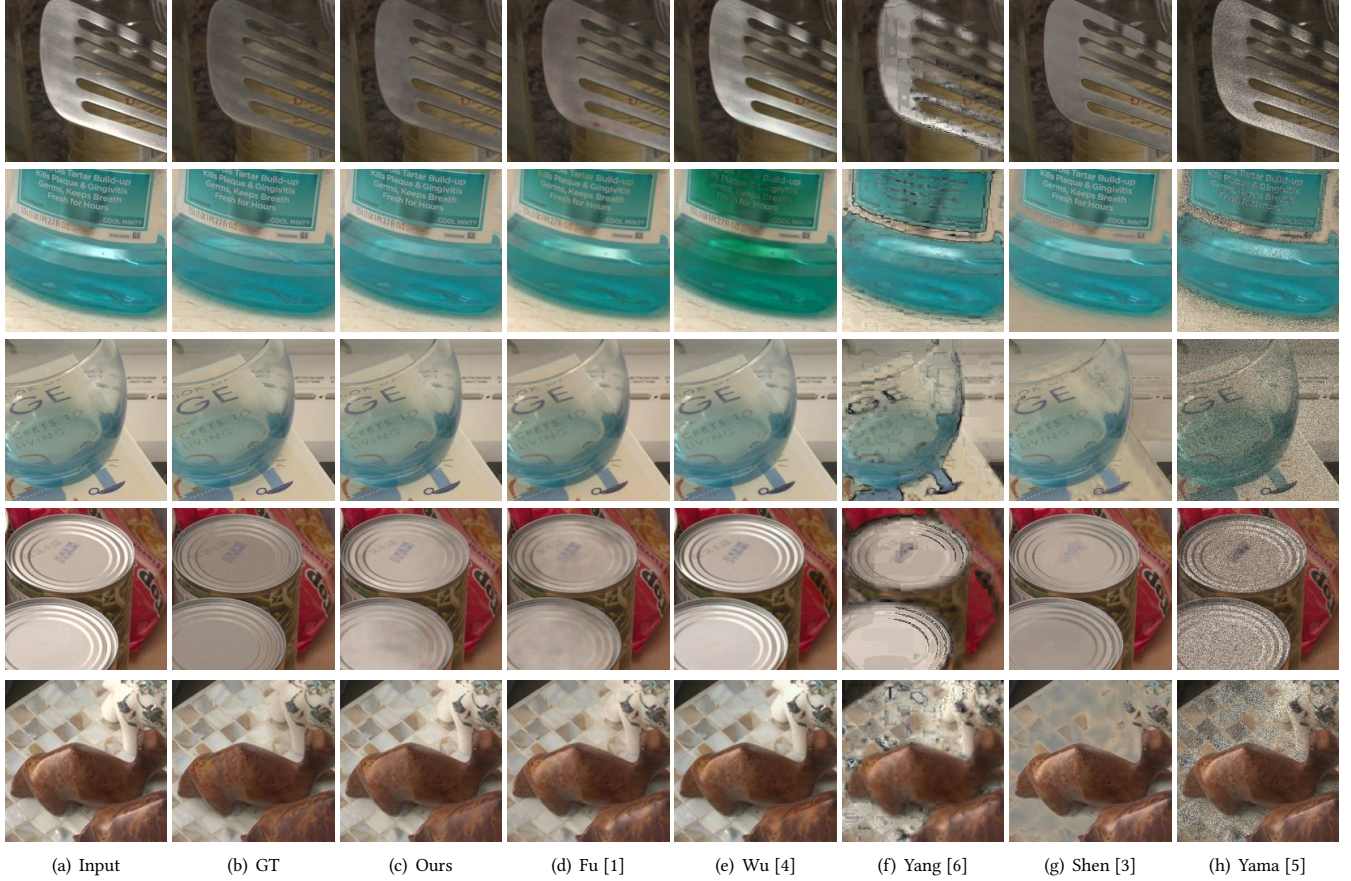


Figure 3: Visual comparison of our method against state-of-the-art highlight removal methods. The highlight images are from SHIQ dataset.



Figure 4: Visual comparison of our method against state-of-the-art highlight removal methods. The highlight images are from our NSH dataset.

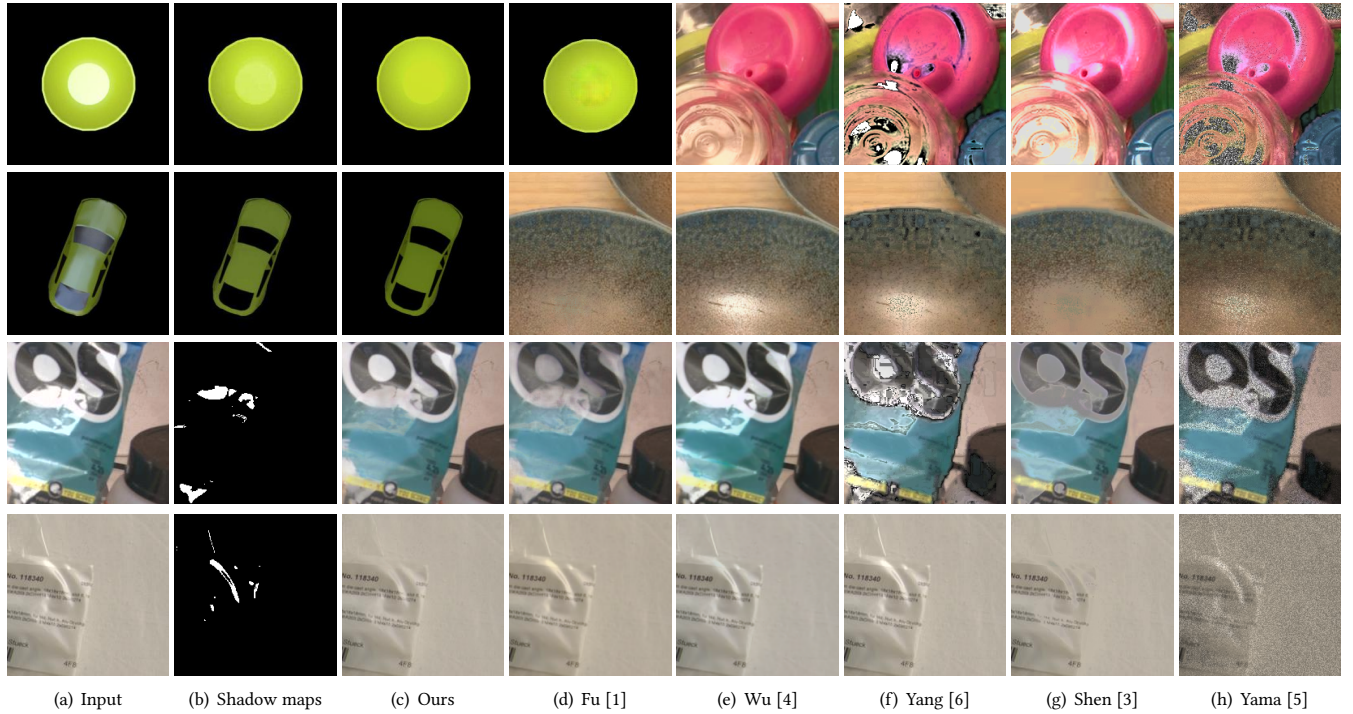


Figure 5: Visual comparison of our method against state-of-the-art highlight removal methods.

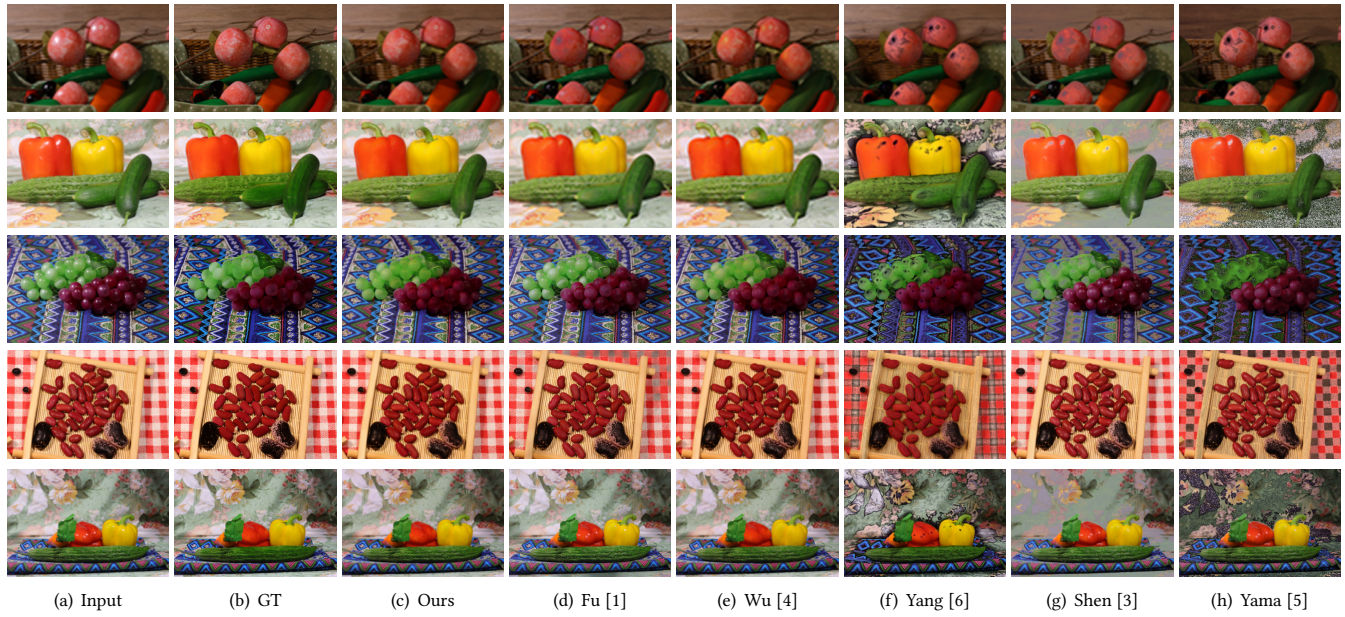


Figure 6: Visual comparison of our method against state-of-the-art highlight removal methods. The highlight images are from PSD dataset.



Figure 7: Visual comparison of our method against state-of-the-art highlight removal methods. The highlight images are from PSD dataset.