Supplementary Material of "Controlling the Rain: from Removal to Rendering"

Siqi Ni, Xueyun Cao, Tao Yue, Xuemei Hu
School of Electronic Science and Engineering, Nanjing University, Nanjing, China
nisiqi@smail.nju.edu.cn, caoxueyun@smail.nju.edu.cn, yuetao@nju.edu.cn, xuemeihu@nju.edu.cn

1. Visualization of Multi-level Interpolation

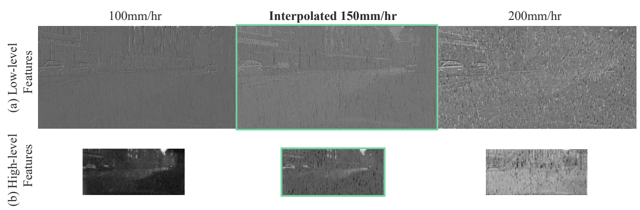

Figure 1. Visualization of features in different levels. The features of interpolated intensity are marked with the green boxes. (a) Low-level interpolated features present more details. (b) High-level interpolated features contain more structure characteristics.

For better understanding our multi-level interpolation, we visualize the interpolated features in PGM, as marked with the green boxes in Fig. 1. They are the interpolation effects of features in two branches of PGM (corresponding to rain intensities of 100mm/hr and 200mm/hr). Then the interpolated features of PGM in different levels are compared. The low-level features are shown in the Fig. 1(a). It can be seen that, the interpolation in low level tends to generate detailed information of intermediate intensity, such as the rain streaks in small scales. While in high-level interpolated features, structure characteristics of intermediate intensity are rendered, such as big rain streaks and the overall background brightness, as shown in Fig. 1(b). Therefore, the interpolation on multiple levels can better extract different features ranging from low level to high level, which promotes the generation of different scales of rain streaks.

2. RainLevel5 Dataset

To show our dataset RainLevel5, we present some examples of rain images and rainless fog images at two different intensities, as shown in Fig. 2.

Considering the limited color diversity of our original training images, during the training of stage II, the input and output rain images are randomly transformed to the other hue with 50% probability in order to realize data augmentation. The rain images with original hue and transformed hue are shown in Fig. 3.

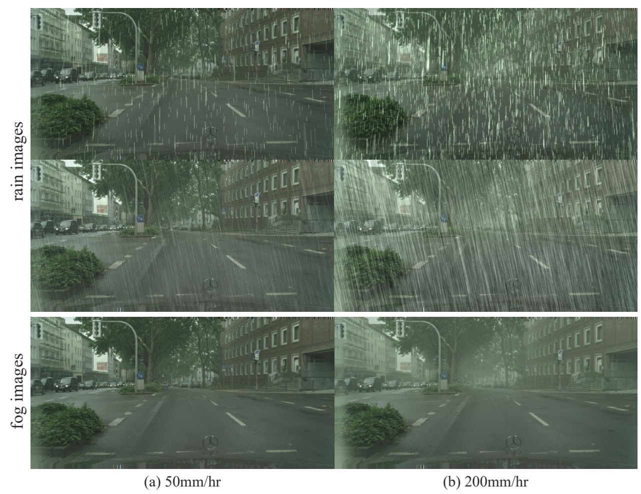

Figure 2. Examples of RainLevel5. Rain and fog images are simulated in 5 intensities, i.e. (a) 50mm/hr and (b) 200mm/hr.

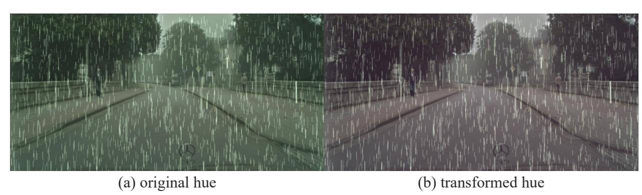

Figure 3. Data augmentation during training by random selection of (a) original hue and (b) transformed hue.

3. Ablation Study in Rain Removal

Table 1. Ablation study in deraining on synthetic datasets.

RainLevel5				
Methods	No DB	Random	Incremental	**Ours**
PSNR	35.78	36.13	35.38	37.81
SSIM	0.982	0.976	0.981	0.985
Rain12000 [1]				
Methods	No DB	Random	Incremental	**Ours**
PSNR	32.13	32.23	32.50	32.67
SSIM	0.883	0.884	0.888	0.892

Effectiveness of Network Architecture To prove the deraining ability of the dense blocks in the coarse module of BEN, the results without the dense blocks are shown in Table 1 (represented as No DB). Both in the two synthetic datasets, our final architecture (**Ours**) gets better deraining results in PSNR and SSIM.

Effectiveness of Decremental Training The rain removal effects of random, incremental and our decremental training strategies are also compared. As shown in Table 1, both the results of random and incremental training strategy are inferior to our method, which further demonstrates the ability of the decremental training strategy in bringing a better deraining performance.

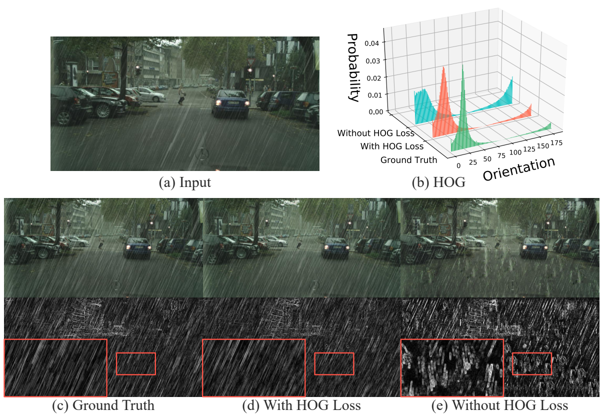

Figure 4. Comparison of results w/o HOG loss. (a) Input rain image, (b) comparison in HOG among gradient images of (c) ground truth, (d) result with HOG loss, and (e) result without HOG loss.

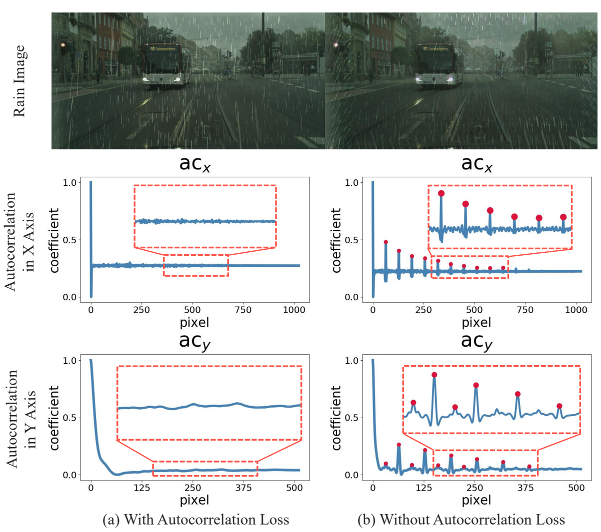

Figure 5. Comparison of results w/o autocorrelation loss. The rain image and corresponding autocorrelation along x and y direction are compared between the result (a) with autocorrelation loss, and (b) without autocorrelation loss (peaks marked with red points).

4. Ablation Study of Loss Function

In this section, we further demonstrate and illustrate the effectiveness of our HOG loss and autocorrelation loss. As shown in Fig. 4, the result with HOG loss shows a more similar orientation distribution with the ground truth, compared with the one without HOG loss. It can also be seen in the HOG comparison in Fig. 4(b). Additionally, as shown in Fig. 5, fewer repetitive rain streaks appear with the autocorrelation loss, which is also demonstrated in the smoother autocorrelation curve in Fig. 5(a), compared with the obvious peaks in Fig. 5(b).

5. Comparison of BEN and MCN at 0 intensity

We compare the deraining results of BEN and MCN at 0 intensity in Tab. 2. As shown, the PSNR/SSIM of BEN and MCN (0mm/hr rain) are almost the same. MCN at 0 intensity achieves better performance on perceptual metric compared with BEN because the training of MCN at intensity 0 alternates with the training at other intensities, which introduces more information of photorealism. Note that for NIQE, the smaller the better.

Table 2. Comparisons between BEN and MCN at intensity 0.

Metric	PSNR	SSIM	NIQE	FSIM
BEN	**37.81**	**0.985**	2.766	0.983
MCN	37.28	0.972	**2.664**	**0.986**

6. More Results on Real and Synthetic Data

To further demonstrate the rain controlling ability of our method, here we show more rain control results in Fig. 6. As can be observed, ranging from rain images in real world to synthetic rain images in RainLevel5 and Rain12000 [1], with a single rain image as input, the intensity of rain can be adjusted arbitrarily, with the same scene-specific characteristics as the input rain image.

References

[1] He Zhang and Vishal M Patel. Density-aware single image de-raining using a multi-stream dense network. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 695–704, 2018.

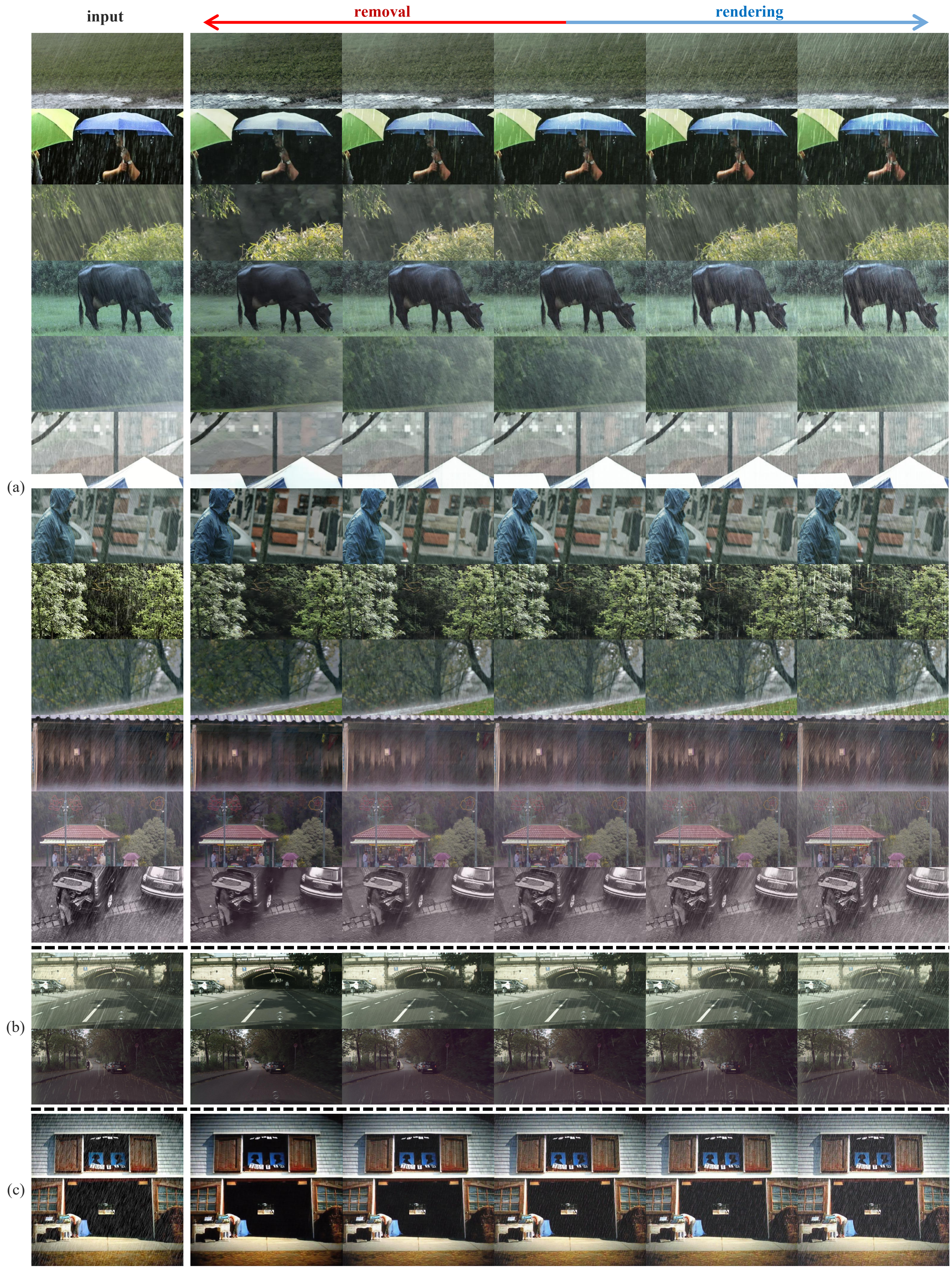

Figure 6. Bi-directional rain control results on (a) real-world rain images and synthetic rain images in (b) RainLevel5 and (c) Rain12000 [1].