Supplemental Material for
Detail-recovery Image Deraining via Context Aggregation Networks

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This supplemental material contains four parts as follows:

1. Additional visual comparisons between before and after integrating Detail Repair Network (DRN) into the state-of-the-arts.
2. Additional quantitative comparisons between before and after integrating DRN into the state-of-the-arts.
3. Additional validations of the squeeze-and-excitation (SE) operation.
4. Further details of DRN architecture.

1. Additional Visual Comparisons

Image deraining commonly involves the estimation of two components: rain streaks and image details. Learning both components simultaneously by a single network is somewhat challenging. Our detail repair network (DRN) can facilitate the state-of-the-art deraining methods of single network for image detail recovery. We have shown some results in Section 4.4 of the submitted manuscript.

In this section, visual results are provided for better understanding on the effectiveness of the proposed detail recovery mechanism.

As evidenced by deraining results of different networks with and without the detail repair network shown in Fig. 1, Fig. 2 and Fig. 3, deraining networks (i.e, DDN [1] and SPA [2]) enhanced by our detail repair network produce much better results in both detail preservation and artifact removal.

Deraining networks tend to lose details which share similar properties with rain streaks, such as the zebra-stripe in Fig. 1 and the fishing rod in Fig. 2. We demonstrate that, by simply incorporating our detail repair network, these lost details can be easily added back to restore high-quality rain-free images.

2. Additional Quantitative Comparisons

In this section, more quantitative results are provided in Table 1 to demonstrate the effectiveness of our proposed detail recovery mechanism.

We compare the PSNR and the running time of deraining methods with and without our detail recovery mechanism on different datasets as shown in Table 1. It is observed that attaching our detail repair network considerably improves the PSNR while sacrificing negligible time efficiency.

Table 1. Quantitative evaluation, DDN w DRN indicates DDN incorporated with the detail repair network.

Datasets	Metrics	DDN	DDN w DRN	SPA	SPA w DRN
Rain200H	PSNR	24.64	25.92	23.04	25.68
	Time	0.03s	0.15s	0.06s	0.45s
Rain800	PSNR	24.04	25.13	22.41	25.67
	Time	0.05s	0.14s	0.26s	0.35s

3. Analysis on SE

To obtain insight on the correlation between the SE weight and the content of layers, we visualize the feature maps with different weights as shown in Fig. 4. It can be clearly observed that the feature maps with more spatial contextual information have received a higher weight as expected.

4. Additional Details of Our DRN's Structure

The detailed structure of the detail repair network is presented in Table 2, illustrating how the receptive field grows by applying the SDCAB block with multi-scale dilations.

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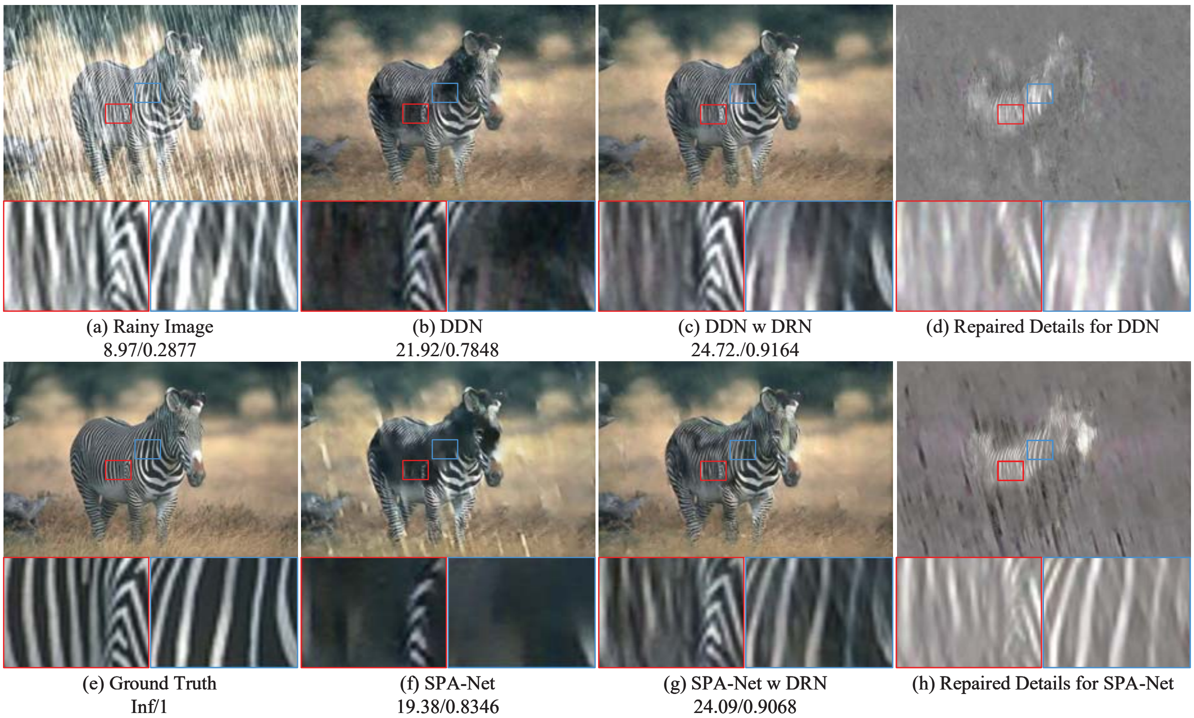

Figure 1. Image deraining performance on dataset Rain200H. From (a)-(h): (a) the rainy image Zebra, the deraining results of (b) DDN [1], (c) DDN with Detail Repair Network, (f) SPA-Net [2], (g) SPA-Net with Detail Repair Network, (d) and (h) are the repaired details of DDN and SPA-Net, and (e) the ground-truth image.

Figure 2. Image deraining performance on dataset Rain200H. From (a)-(h): (a) the rainy image Car, the deraining results of (b) DDN [1], (c) DDN with Detail Repair Network, (f) SPA-Net [2], (g) SPA-Net with Detail Repair Network, (d) and (h) are the repaired details of DDN and SPA-Net, and (e) the ground-truth image.

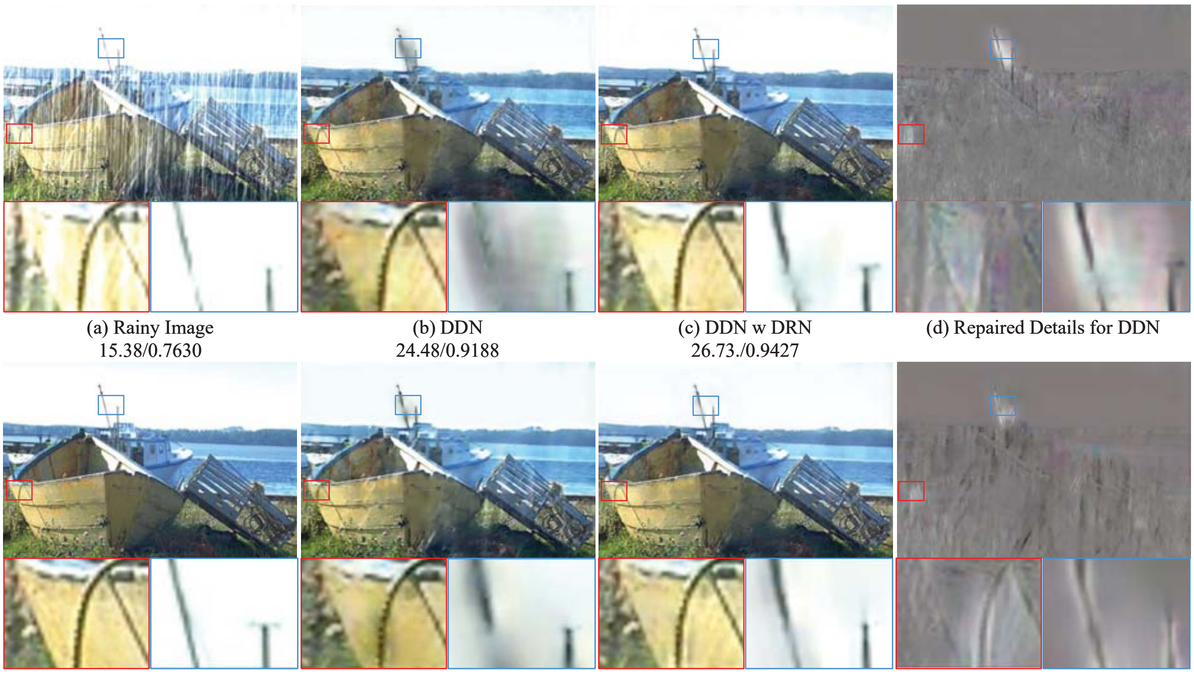

Figure 3. Image deraining performance on dataset Rain200H. From (a)-(h): (a) the rainy image Boat, the deraining results of (b) DDN [1], (c) DDN with Detail Repair Network, (f) SPA-Net [2], (g) SPA-Net with Detail Repair Network, (d) and (h) are the repaired details of DDN and SPA-Net, and (e) the ground-truth image.

Table 2. The detailed architecture of the detail repair network.

Layer	0	1	2	...	d	...	16	17	18
Convolution	3×3	3×3	3×3	...	3×3	...	3×3	3×3	3×3
SDCAB	No	Yes	Yes	...	Yes	...	Yes	No	No
Dilation	1	7	7	...	7	...	7	1	1
Receptive field	3×3	17×17	31×31	...	$(d-1) \times 14 + 17$	...	227×227	229×229	231×231

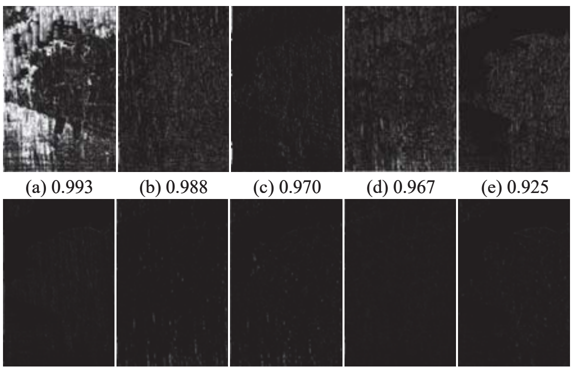

Figure 4. Feature maps with different weights. The images in (a)-(e) denote the top five high weighted feature maps, and the images in (f)-(i) denote the top five low weighted feature maps.

References

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[2] Tianyu Wang, Xin Yang, Ke Xu, Shaozhe Chen, Qiang Zhang, and Rynson WH Lau. Spatial attentive single-image deraining with a high quality real rain dataset. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 12270–12279, 2019. 1, 2, 3