Supplementary Material for
Random Sub-Samples Generation for Self-Supervised Real Image Denoising

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Testing strategy	RSG	PD
SDAP	36.19/0.8585	**36.58/0.8630**
SDAP (E)	37.22/0.8926	**37.30/0.8937**

Table 1: The effect of different testing strategies on PSNR(dB)/SSIM.

1. RSG for Testing

To evaluate the impact of our RSG strategy on the test, we replace PD with RSG in the testing stage. Table 1 shows the PSNR and SSIM results in the SIDD validation dataset [1] for different testing methods.

In training, RSG generates a larger quantity of training data with more varied random sampling differences as compared to PD. Thus, RSG can achieve better results when used for training. However, in testing, while sampling helps to break the spatial correlation of noise pixels, it also reduces the spatial correlation of signal pixels to some degree. As a result of its random sampling step, the RSG strategy tends to have a more negative impact on the spatial correlation of signal pixels, which can result in a decline in BSN denoising performance. Consequently, the performance of testing with RSG is inferior to that of testing with PD.

Since the sub-samples generated by RSG are different each time, the strategy of averaging after multiple denoising can be used to achieve better performance of the final denoising results. Therefore, we use RSG n times for testing and average the results before enhancement. This performance enhancement method is denoted by "n RSG + enhancement", which is shown schematically in Figure 1. "n RSG" means that no enhancement is performed and the denoising results are averaged directly. Table 2 shows the effect of different "n" values on the PSNR results when RSG is used for testing.

The results shown in Table 2 verify that the using "single PD + augmentation" (SDAP (S)(E)) in testing is always better than RSG. Therefore, we use PD strategy instead of RSG strategy in testing.

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n	1	2	3	4	5	6	7	8
n RSG	36.19	36.52	36.64	36.70	36.74	36.76	36.78	36.79
n RSG + enhancement	37.22	37.24	37.25	37.25	37.25	37.25	37.25	37.25

Table 2: The effect of different "n" values on PSNR(dB).

2. More Results on Real-world Datasets

In Figures 3 and 4, we show more denoising results on the SIDD validation dataset [1] and DND benchmark [7].

3. Limitations

In Figure 2, we illustrate the limitation of our method. Small details in some images are more likely to be considered as noise after being sampled by PD. BSN denoising masks the center pixel, which also causes some image details to be ignored. Since our method uses the PD strategy and uses BSN to denoise the noisy image twice in succession, some small details in the image may be smoothed to some extent. Over-smoothing of details is also a drawback of many unsupervised methods. We still need to continue to work on it, although the results of our method are better than others. For the future work, we hope to obtain better image details using the proposed self-supervised method.

References

[1] Abdelrahman Abdelhamed, Stephen Lin, and Michael S Brown. A high-quality denoising dataset for smartphone cameras. In *CVPR*, pages 1692–1700, 2018.

[2] Kostadin Dabov, Alessandro Foi, Vladimir Katkovnik, and Karen Egiazarian. Image denoising by sparse 3-d transform-domain collaborative filtering. *IEEE TIP*, 16(8):2080–2095, 2007.

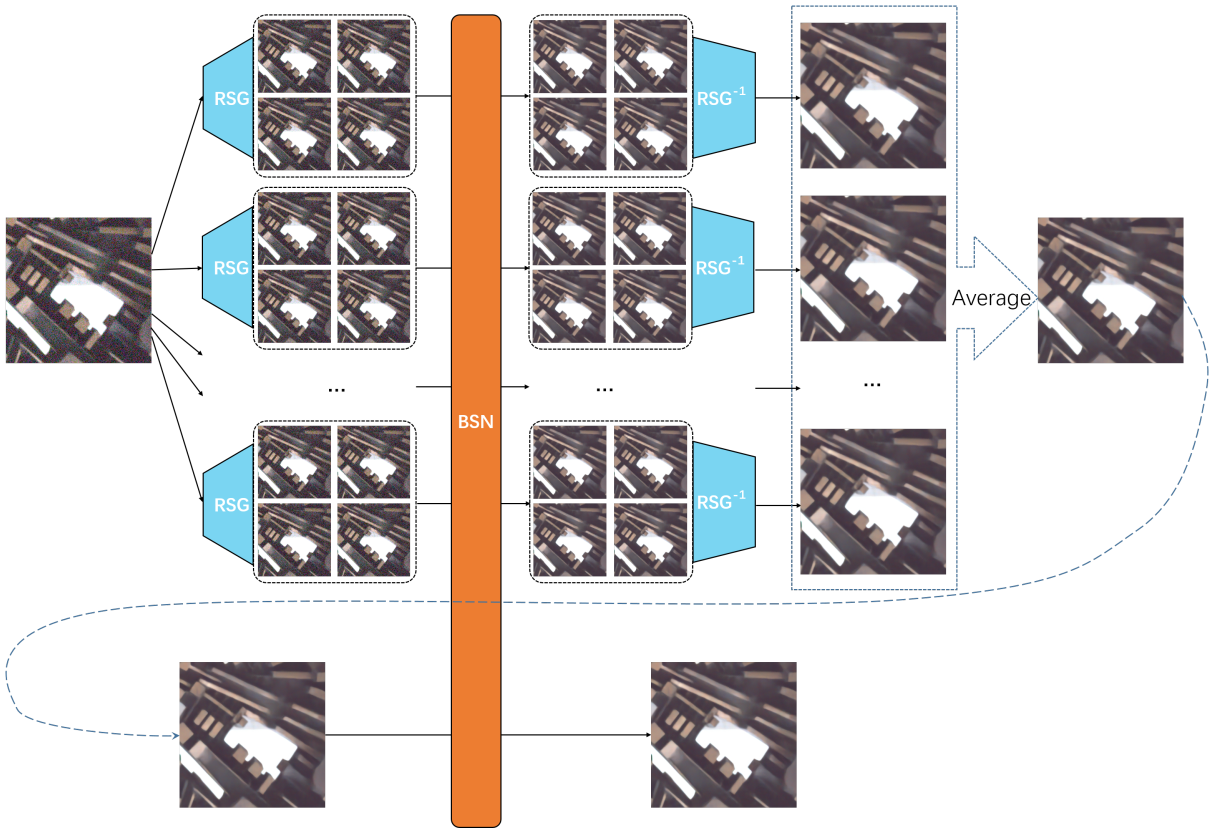

Figure 1: Overview of “n RSG + enhancement” for testing. RSG^{-1} is the inverse operator of RSG.

[3] Shi Guo, Zifei Yan, Kai Zhang, Wangmeng Zuo, and Lei Zhang. Toward convolutional blind denoising of real photographs. In *CVPR*, pages 1712–1722, 2019.

[4] Geonwoon Jang, Wooseok Lee, Sanghyun Son, and Kyoung Mu Lee. C2n: Practical generative noise modeling for real-world denoising. In *ICCV*, pages 2350–2359, 2021.

[5] Wooseok Lee, Sanghyun Son, and Kyoung Mu Lee. Ap-bsn: Self-supervised denoising for real-world images via asymmetric pd and blind-spot network. In *CVPR*, pages 17725–17734, 2022.

[6] Reyhaneh Neshatavar, Mohsen Yavartanoo, Sanghyun Son, and Kyoung Mu Lee. Cvf-sid: Cyclic multi-variate function for self-supervised image denoising by disentangling noise from image. In *CVPR*, pages 17583–17591, 2022.

[7] Tobias Plotz and Stefan Roth. Benchmarking denoising algorithms with real photographs. In *CVPR*, pages 1586–1595, 2017.

[8] Kai Zhang, Wangmeng Zuo, Yunjin Chen, Deyu Meng, and Lei Zhang. Beyond a gaussian denoiser: Residual learning of deep cnn for image denoising. *IEEE TIP*, 26(7):3142–3155, 2017.

(a) Noisy (b) SDAP (S)(E)

Figure 2: The limitations of our method. It can be seen that the denoising results of our method are relatively smooth to some extent.

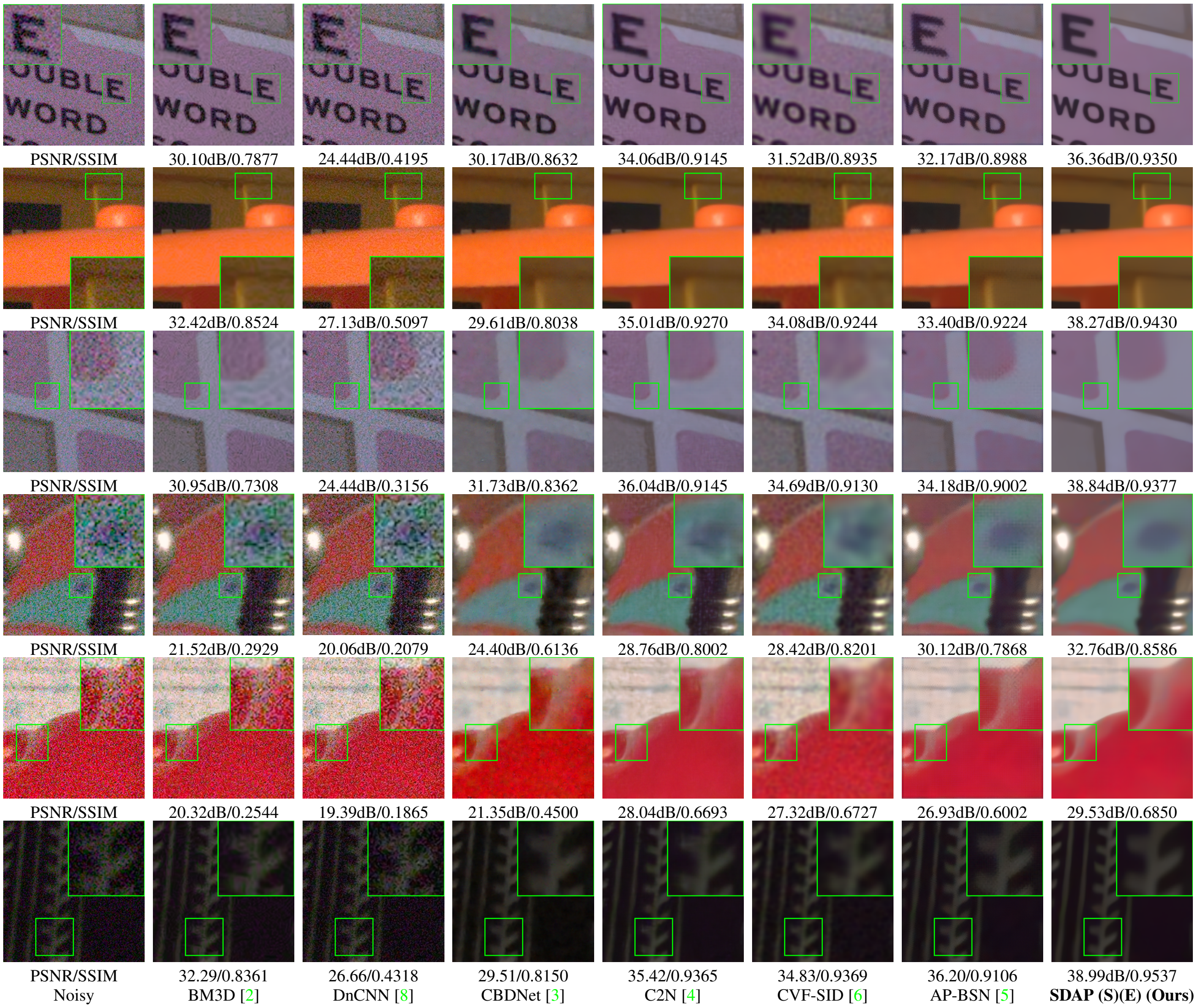

Figure 3: Visual comparison on the SIDD validation dataset.

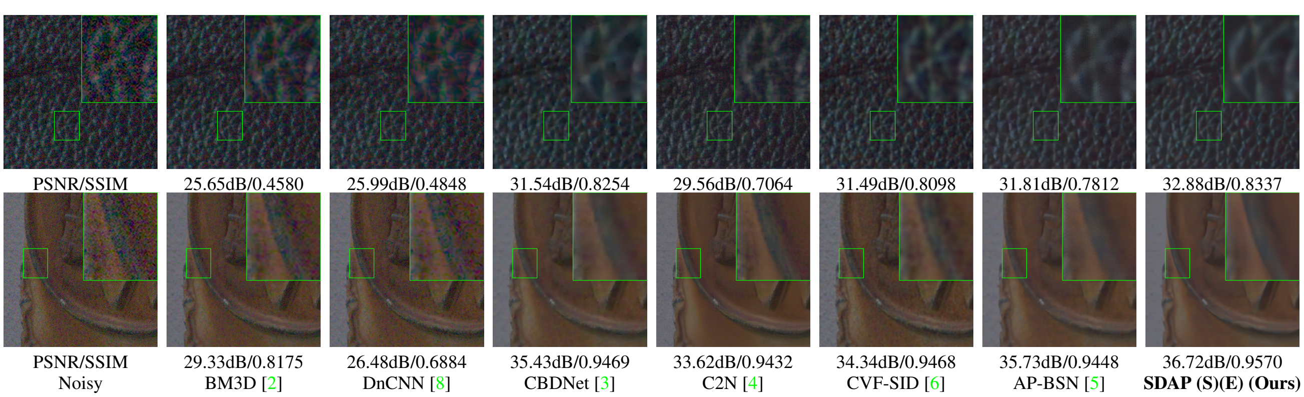

Figure 4: Denoising examples from DND benchmark.