Unsupervised Image Denoising in Real-World Scenarios via Self-Collaboration Parallel Generative Adversarial Branches

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0. Overview

The following items are contained in the Supplementary Material:

1. Specific structures of our basic modules.

2. Parameter setting of sharpening technique in our discriminator.

3. Parameter number.

4. Specific structures of five variants in sub-section 4.3.

5. Visual comparision of different variants in sub-section 4.3 and 4.5.

6. More qualitative results.

7. Test on other datasets.

1. Specific Structures of Our Basic Modules

1) Generative Network Architecture. The purpose of the generator is to synthesize a noisy image that matches the real noise distribution from a clean image. The generative network architecture is shown in Figure 1. Specifically, three convolutional layers followed by LeakyReLU are contained at both the beginnings and end of the network. In addition, six convolutional residual blocks are included in the middle part of the generator.

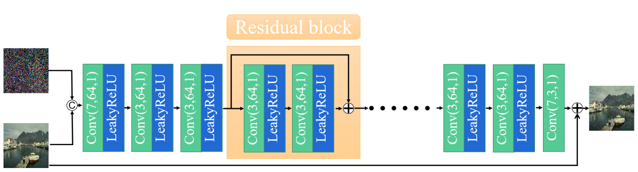

Figure 1. The generative network of our SCPGabNet

2) Discriminative Network Architecture. The discriminator prompts the generator to synthesize real images through adversarial training, making the simulated distribution closer to the real distribution. As shown in Figure 2, we use the "Patch-GAN"[12] structure as our discriminator network. It maps the input samples onto a matrix, which is the feature map of the convolutional layer output. Each element in the matrix describes the probability that a local region in the input sample is coming from a real noisy image. This strategy allows the discriminator to focus more on the local areas, and makes the training more valid.

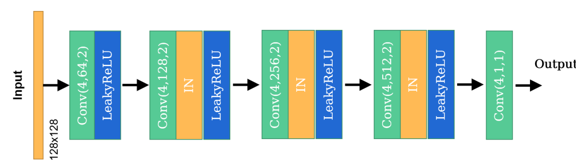

Figure 2. The discriminative network of our SCPGabNet.

3) Denoising Network Architecture. The denoising network [9] is a trainable and extended version of the ACP-driven denoising problem. It consists of a feature domain (FD) module and a reconstruction module. In Figure 3, K denotes the stage of iteration and dual element-wise attention mechanism (DEAM) modules. Besides, $*$ and # denote the parameters of these modules are shared, respectively.

4) Complete SCPGabNet Framework. The SCPGabNet framework is presented in Figure 2 of the main document without showing the discriminators for simplicity. In this Supplementary Material, the more detailed architecture of SCPGabNet with discriminators is shown in Figure 4.

2. Parameter Setting of Sharpening Technique in Our Discriminator

The sharpening technique has a great effect on the performance of the discriminator. The weight of the sharpening layer in our discriminator is fixed, and its filtering operator is implemented by Gaussian blurring. Inspired by [2], the Gaussian blurring kernel size and standard deviation are

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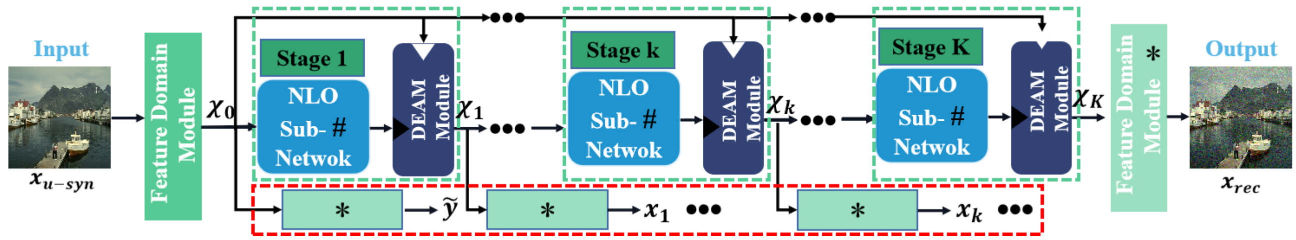

Figure 3. The denoising network of our SCPGabNet.

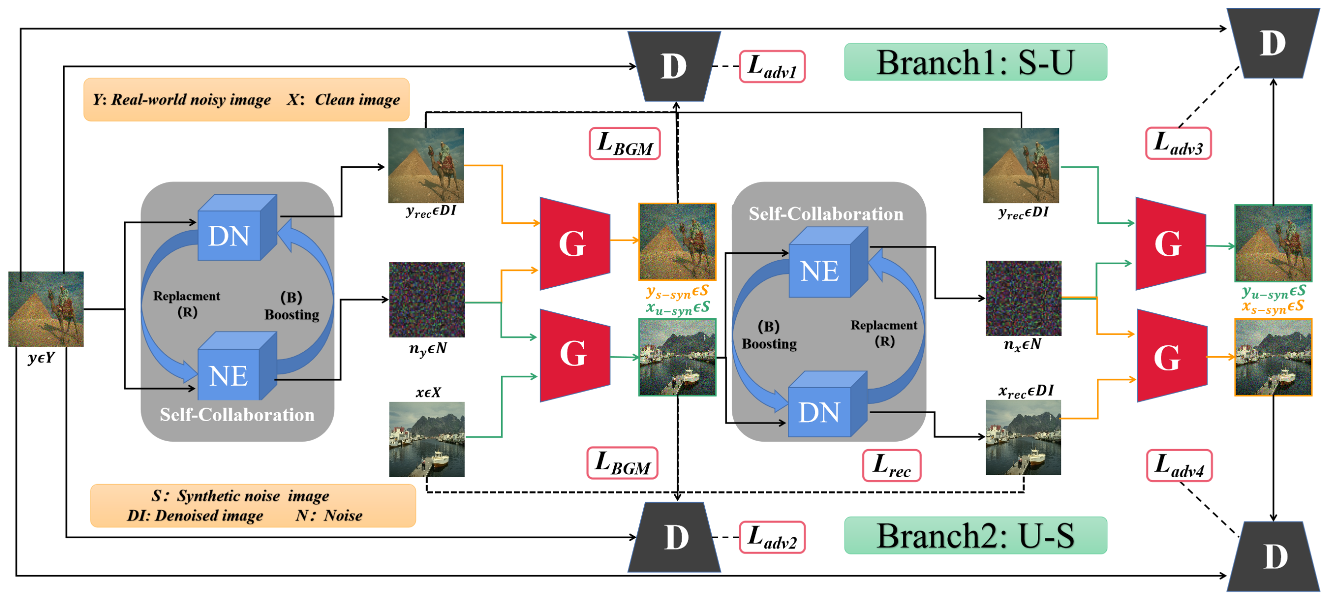

Figure 4. The more detailed architecture of our proposed SCPGabNet framework (compared with the simplified one, i.e., Figure 2, in the main document) with discriminator.

empirically set to 15 and 9, respectively.

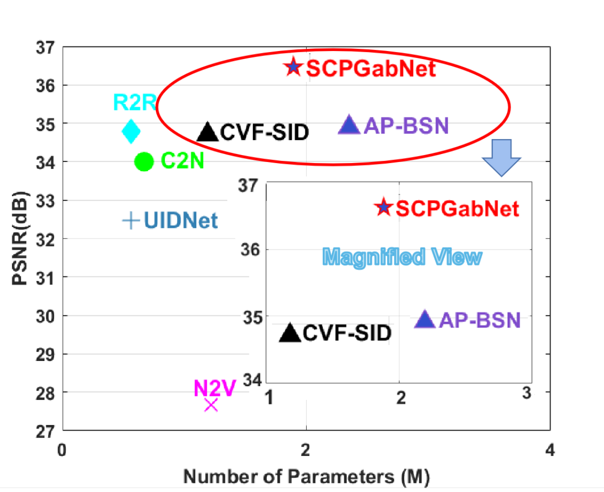

Figure 5. The numbers of parameter and average PSNR values of different methods on the SIDD Benchmark.

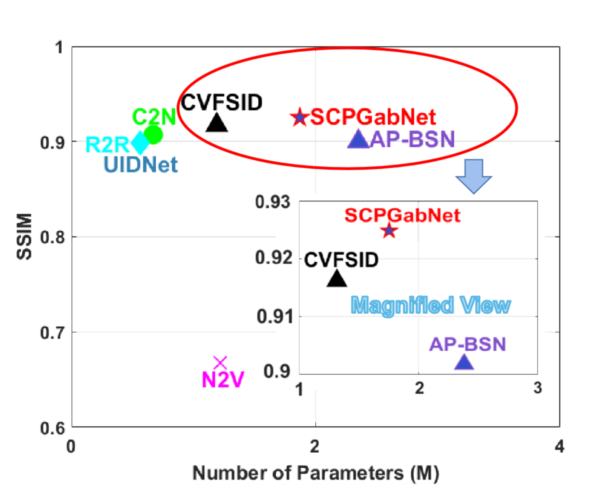

Figure 6. The numbers of parameter and average SSIM values of different methods on the SIDD Benchmark.

3. Parameter Number

To evaluate the comprehensive performance of these representative and latest unsupervised denoising methods [4, 3, 8, 1, 6, 5, 8], we show the trade-off between the parameters number and the performance of different denoising methods on the SIDD Benchmark dataset. The numbers of the parameter with the average PSNRs and SSIMs of different algorithms are visualized in Figures 5 and 6. Compared with other advanced and competitive unsupervised denoising methods, our SCPGabNet achieves the best performance with a moderate parameter number and the highest PSNR and SIMM values.

4. Specific Structure of Five Variants in Sub-section 4.3

To verify the influence of the PGabNet structure, five comparative variants are tested. Since the experimental results have been reported in sub-section 4.3, we mainly describe their specific structures in this sub-section, as shown in Figures 7, 8, 9, 10, 11. The V1 is the GAN-based unsupervised denoising network with unpaired synthesis; the V2 is the V1 + BGMloss; the third is the V2 + NE module; the V4 is the V3 + self-synthesis, i.e., SGabNet; and the V5 is our PGabNet.

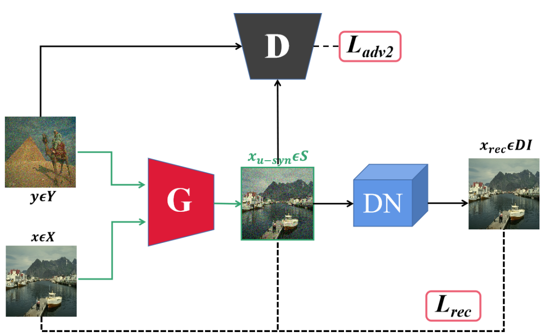

Figure 7. **V1** - the GAN-based unsupervised denoising network only with unpaired synthesis.

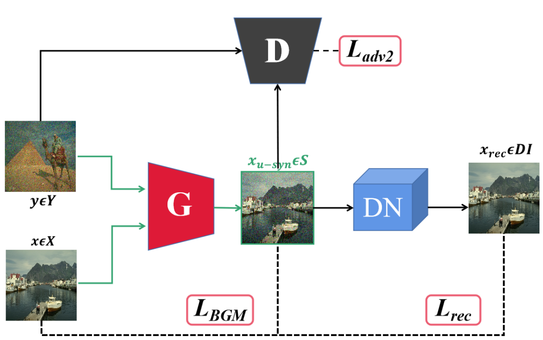

Figure 8. **V2** - V1 + BGMloss.

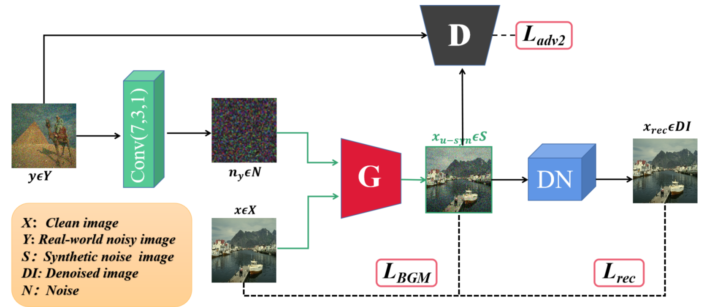

Figure 9. **V3** - V2 + NE module.

5. Visual Comparision of Different Variants in Sub-sections 4.3 and 4.5

In sub-section 4.4, the objective effectiveness of the SC strategy has been verified by testing the PSNR results of five stages. In this sub-section, we show their visual comparison in Figure 12. In sub-section 4.5, the objective analysis of the transferability has been provided by testing the PSNR results of four different denoisers. In this sub-section, we show their visual comparison in Figure 13. Specifically, we present 4 pairs of denoised images generated from the four denoising networks (i.e., DnCNN[11], UNet[7], DBSNL[10], DeamNet[9]). In each pair, one adopts the SC strategy and the other doesn't. By comparing their results, we can find that the noise is significantly reduced after using the SC strategy. Therefore, the SC strategy has the ability to signficantly improve the performance of various denoisers under the unsupervised denoising framework. Furthermore, it verifies the strong transferability of the SC strategy to other denoising networks.

6. More Qualitative Results

In this sub-section, we provide more results to demonstrate the superiority of our SCPGabNet to other state-of-the-art unsupervised denoising methods. As shown in Figures 14, 15, and 16, it can significantly reduce noise in the denoised images, and the edges and details of the images are also well reconstructed. In contrast, other competing methods may lead to excessive smoothness or produce results with higher remaining noise than ours. Consequently, the effectiveness of our SCPGabNet in both objective and subjective real-world noise reduction are well verified.

7. Test on other datasets

In this sub-section, we provide the results of SCPGabNet and the newest methods in CVPR22 test on PolyU denoising dataset. Although the images from PolyU contains compression effects, the results in Table 1 show that our SCPGabNet achieves better performance than others.

Table 1. Denoising results of several competitive methods on PolyU.

Methods	CVF-SID	AP-BSN	SCPGabNet(Ours)
PSNR(dB)	33.00	34.24	37.14
SSIM	0.9101	0.9392	0.9534

References

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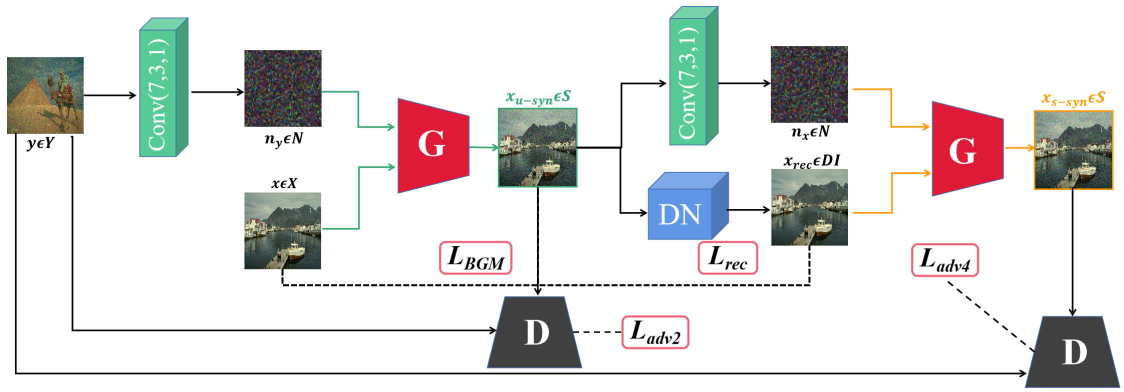

Figure 10. **V4** - V3 + self-synthesis (SGabNet).

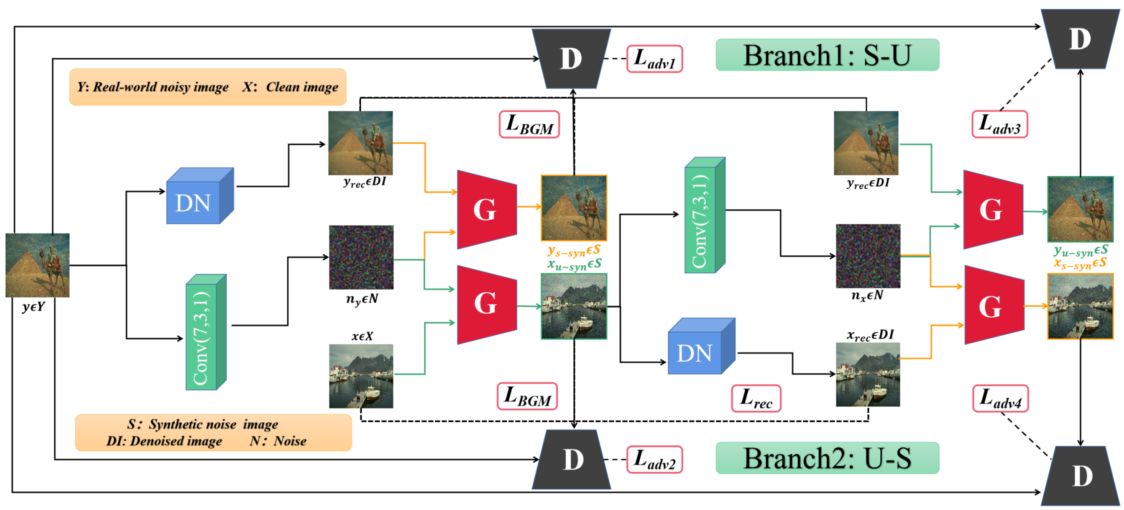

Figure 11. **V5** - PGabNet.

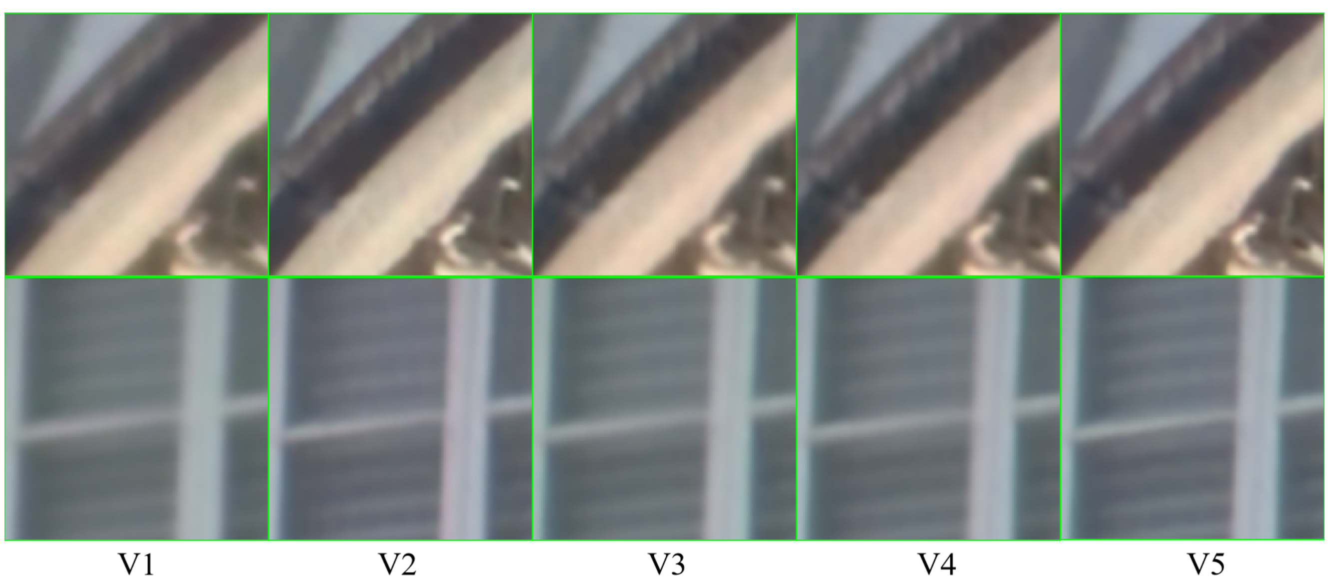

Figure 12. Example of a noisy image from DND Benchmark to test five stages: $V1$: the GAN-based unsupervised denoising network with unpaired synthesis; $V2$: the V1 + BGMloss; $V3$: the V2 + NE module; $V4$: the V3 + self-synthesis, i.e., SGabNet; $V5$: the PGabNet.

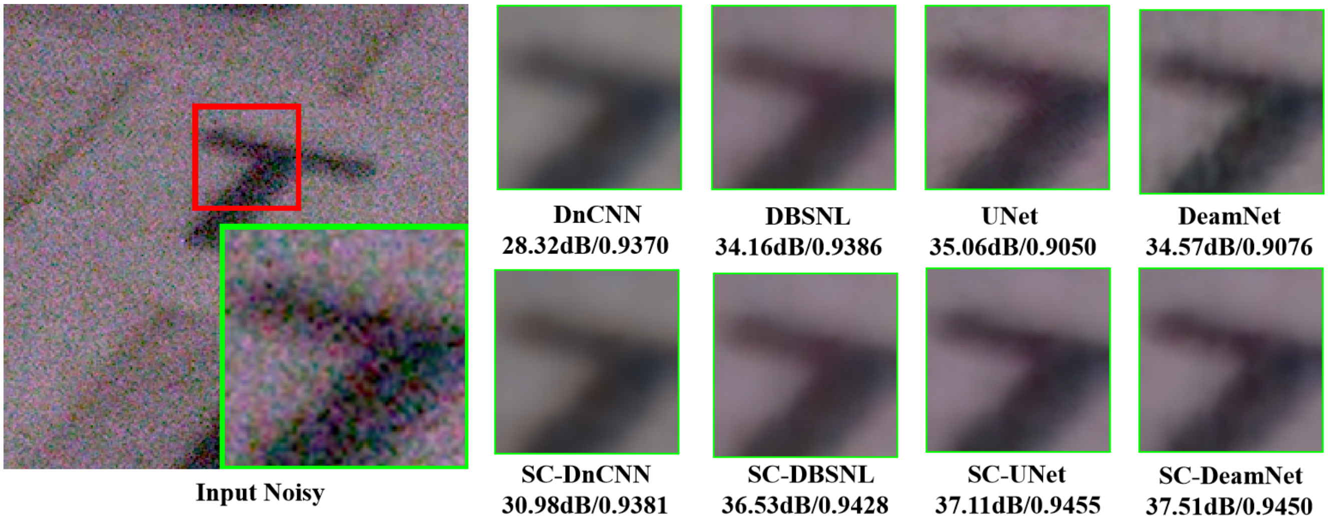

Figure 13. Example of four denoising networks applying SC: DnCNN, DBSNL, UNet, and DeamNet.

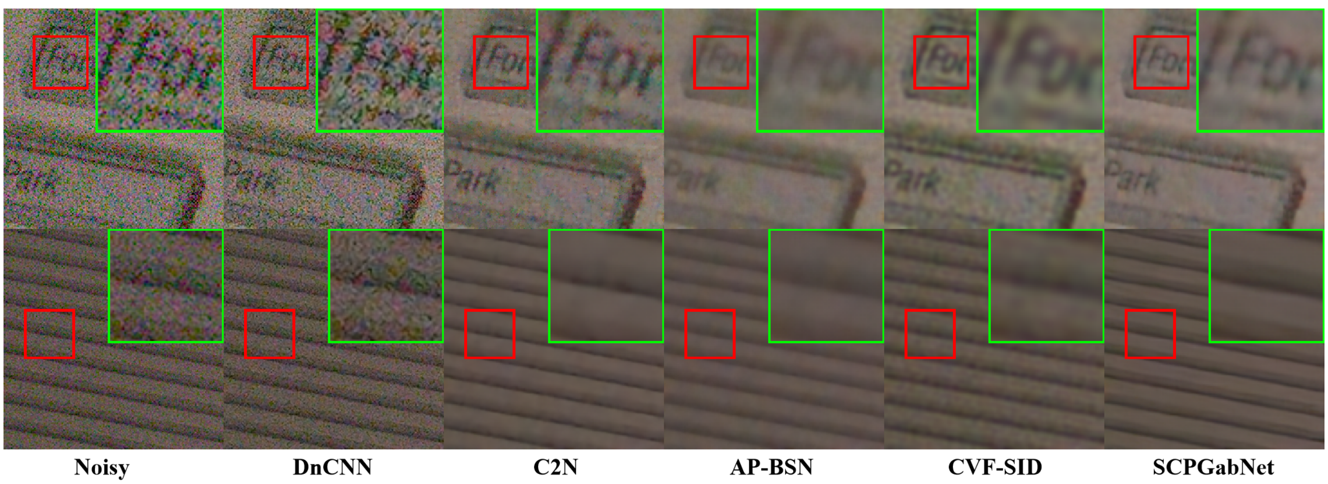

Figure 14. Visual quality comparison for images from SIDD Validation (example 1).

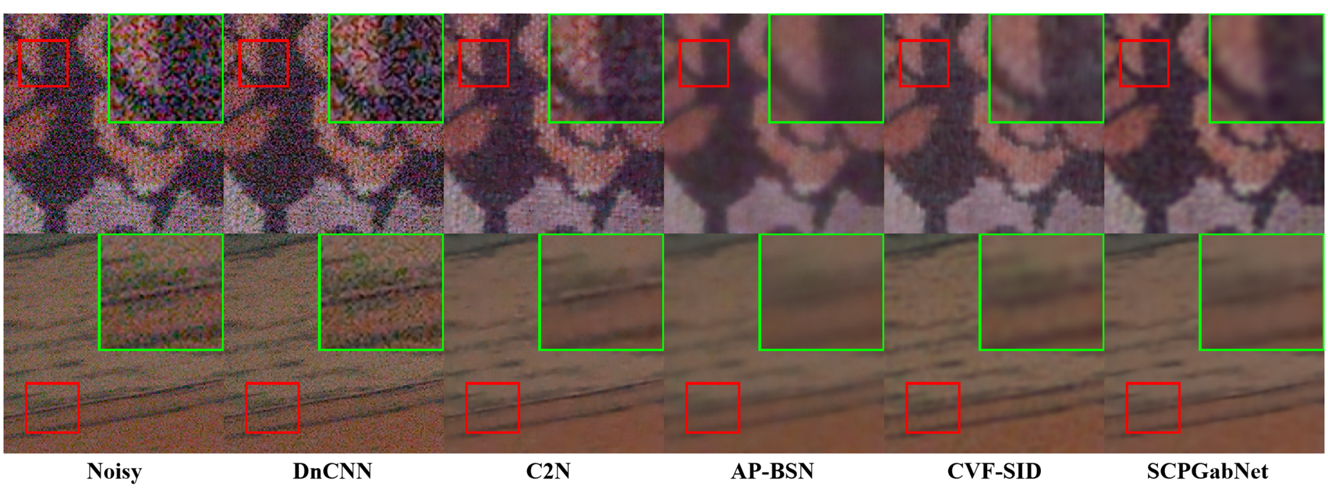

Figure 15. Visual quality comparison for images from SIDD Validation (example 2).

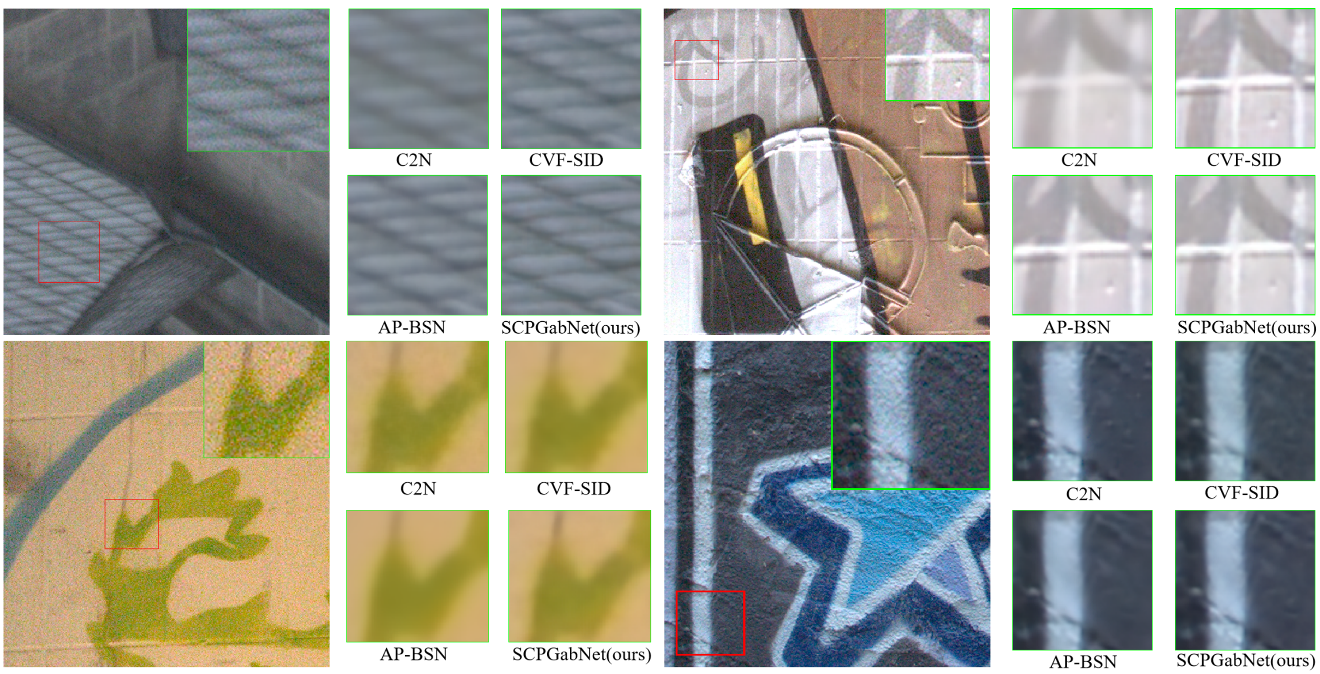

Figure 16. Visual quality comparison for images from DND Benchmark.