Supplementary Material: Toward Interactive Modulation for Photo-Realistic Image Restoration

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Abstract

In this supplementary file, we first provide the analysis of the global feature modulation in the discriminator and the multi-scale architecture in the generator on more degradations in section 1 and section 2, respectively. Section 3 contains qualitative modulation results on real-world images using the proposed CUGAN. Then, we present more qualitative modulation results for image restoration on synthetic testing data in section 4.

1. The Effect of Modulation in the Discriminator.

We use global feature modulation (GFM) in the discriminator. To demonstrate its effectiveness, we provide more results in LPIPS on more degradations evaluated by CBSD68 and LIVE1 datasets. From figure 1, we can observe that the GFM can help the proposed model stably obtain lower LPIPS (better performance) on all degradations.

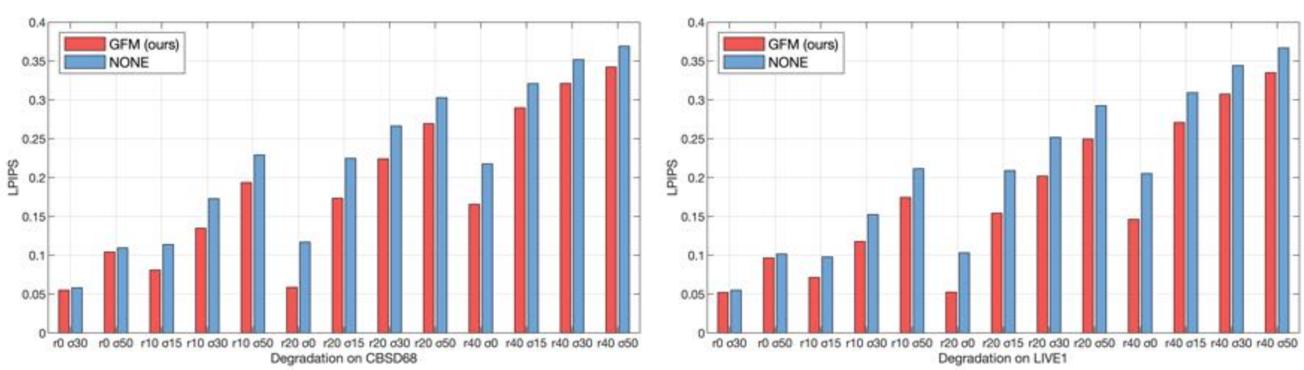

Figure 1. Results achived by CUGAN (red) and CUGAN without GFM (blue) on CBSD68 (left) and LIVE1 (right) dataset. Lower LPIPS indicates better performance.

2. The Effect of Multi-scale Architecture in the Generator.

We implement the multi-scale architecture in the generator. This section provides convergence curves in LPIPS on more degradations evaluated by LIVE1 to show the superiority of multi-scale architecture. As we can see from Figure 2, our

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multi-scale architecture (CUGAN-3) stably brings a large improvement on different degradations compared with CUGAN-1

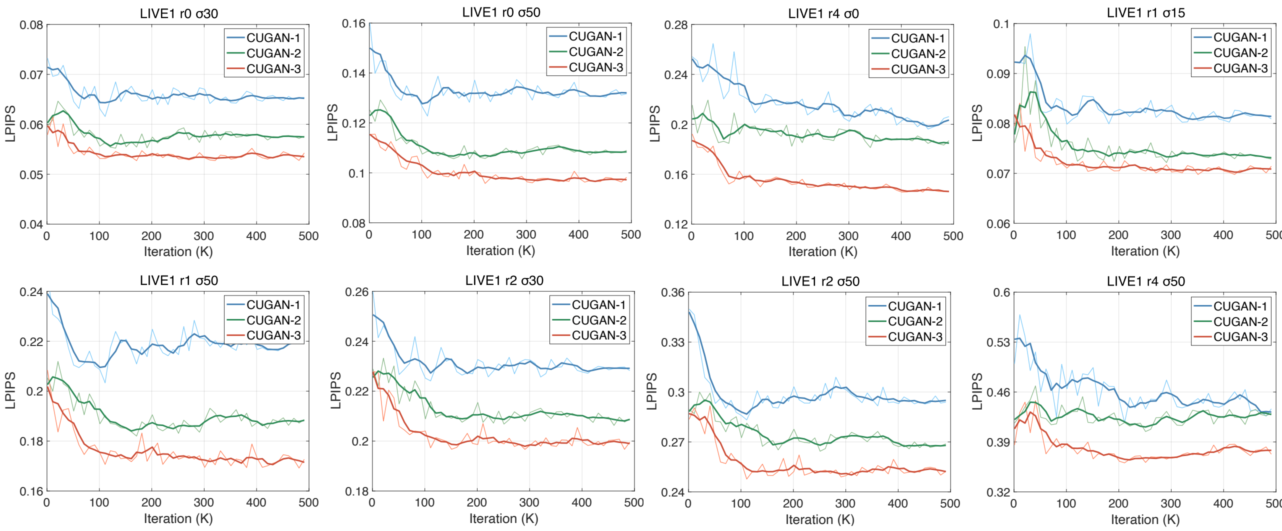

Figure 2. Convergence curves achieved by different models with different number of scales in term of LPIPS on LIVE1 dataset.

3. More Qualitative Modulation Results in real-world images

Here, we present more modulation results (see Figure 3) for image restoration and image super-resolution to show the effectiveness of CUGAN on corrupted images in real-world scenarios. It demonstrates that our CUGAN could deal with real-world images even it is traiend on synthetic dataset.

Figure 3. Modulation for image restoration in real-world images. The input images with unknown noise are from NIND [1] dataset. In the first row, we gradually remove then noise by changig the second element of the condition vector; In the second row, we could further sharpen the restored result by changing the first element.

4. More Qualitative Modulation Results for Image Restoration.

Here, we present more modulation results to show the effectiveness of CUGAN on image restoration task. For denoising, the modulation range is $\sigma \in [0, 50]$, while the deblurring range is $r \in [0, 4]$. In Figure 4, the proposed CUGAN achives modulation in a range of degradations as well as smooth transition between MSE and GAN effects.

References

[1] Benoit Brummer and Christophe De Vleeschouwer. Natural image noise dataset. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*, pages 0–0, 2019. 2

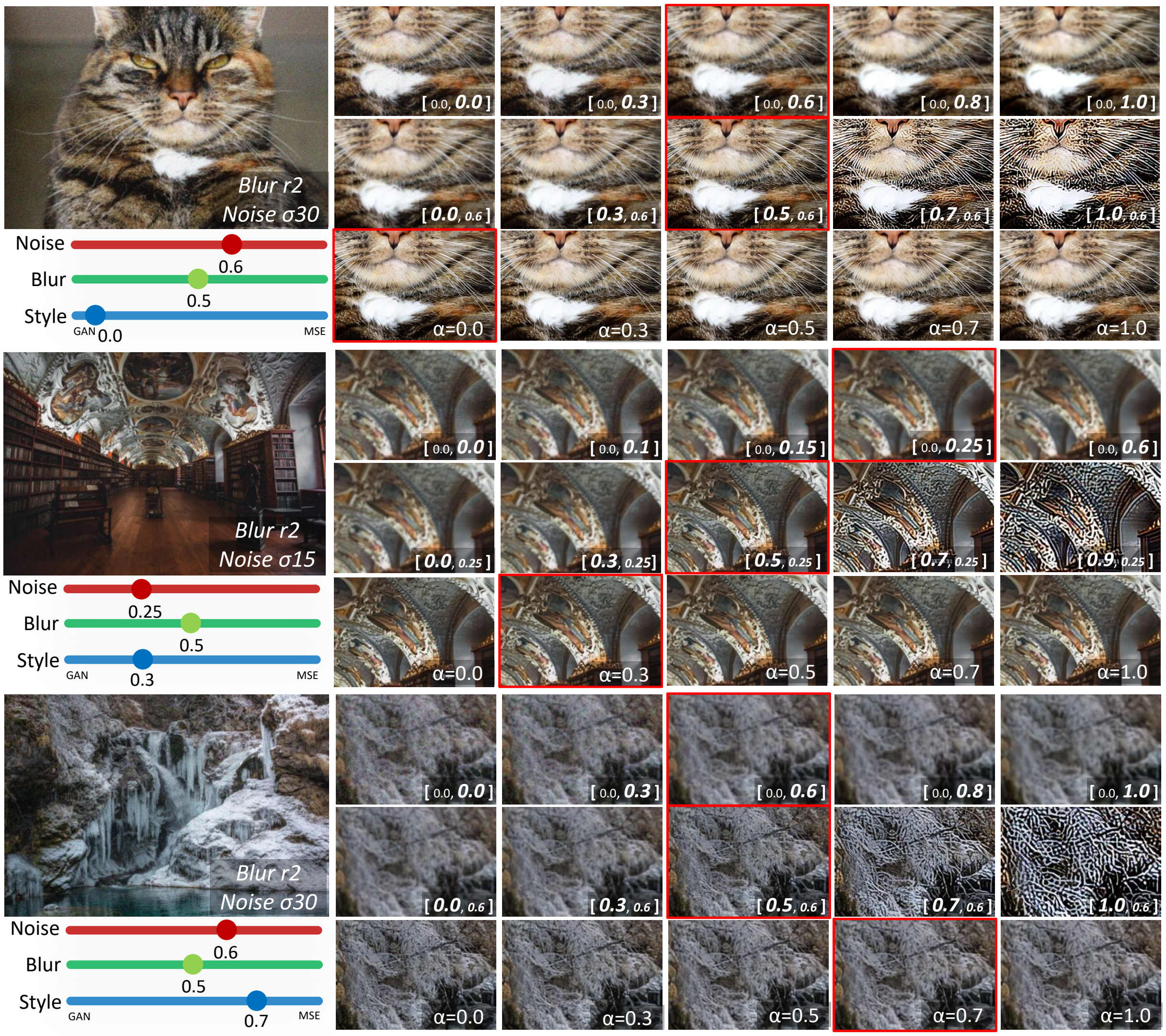

Figure 4. Qualitative Results of Modulation for Image Restoration. The first two rows illustrates the modulation process for different degradations. While the third row illustrate the smooth transition between GAN and MSE effects