Navigating Image Restoration with VAR's Distribution Alignment Prior

Supplementary Material

In the supplementary file, we provide more supporting materials. This supplementary document is organized as follows:

Sec. 1 presents the ablation studies on DAE modules.
Sec. 2 presents more implementation details.
Sec. 3 presents more visual comparison results.

1. Ablation Studies on DAE

We explored the influence of the guidance strength of VAR multi-scale priors on restoration tasks by altering the quantity of DAE modules. The results from Tab. 1 indicate a positive correlation between model performance and the guidance strength provided by VAR priors. This discovery indicates that the multi-scale priors within VAR exhibit notable effectiveness in directing the optimization trajectory of intricate multi-task restoration endeavors, effectively steering the model towards enhancing performance. The training trajectories illustrated in Fig. 1 also support this conclusion, indicating that the integration of DAE modules can accelerate the model's convergence.

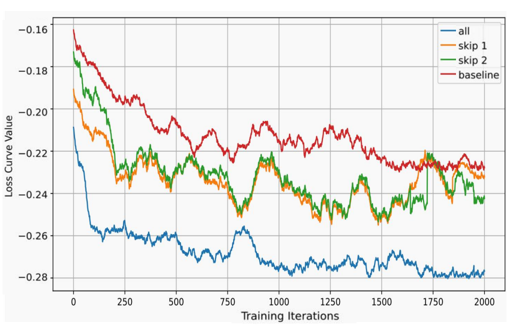

Figure 1. The training trajectory using different number of DAE.

Table 1. Ablation experiments on the DAE number.

Exp.	DAE				PSNR↑	SSIM↑
	all	skip1	skip2	w/o		
a				✓	28.98	0.867
b			✓		29.29	0.883
c		✓			29.49	0.902
d	✓				29.66	0.926

2. More Implementation Details

For the image reconstruction pretraining of VAR, we employ Adam optimizer with a fixed learning rate of 1e-4. We utilize the high-quality images from widely-used DIV2k [1] and Flickr2k [3] to finetune the VAR model pre-trained on ImageNet [2].

3. More Visual Comparison Results

In this section, we provide more visual restoration results in Figs. 2 to 6, exhibits superior visual restoration quality of our method.

References

[1] Eirikur Agustsson and Radu Timofte. Ntire 2017 challenge on single image super-resolution: Dataset and study. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops*, pages 126–135, 2017.

[2] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 248–255, 2009.

[3] Bee Lim, Sanghyun Son, Heewon Kim, Seungjun Nah, and Kyoung Mu Lee. Enhanced deep residual networks for single image super-resolution. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops*, pages 136–144, 2017.

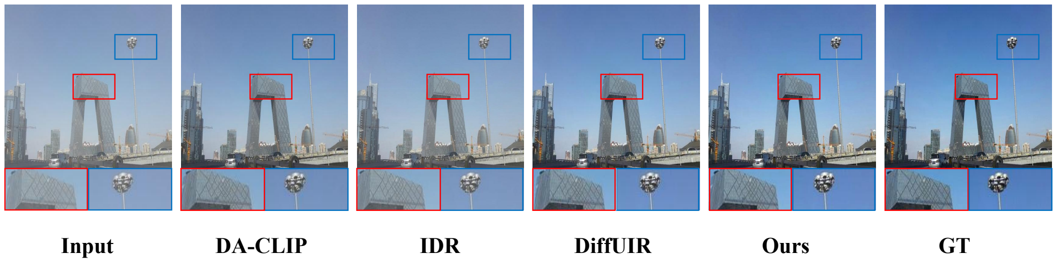

Figure 2. Visual comparison with state-of-the-art universal methods on dehazing task. Please zoom in for details.

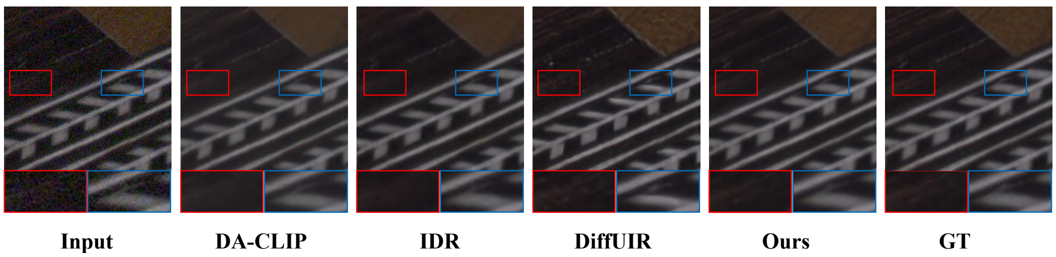

Figure 3. Visual comparison with state-of-the-art universal methods on real image denoising task. Please zoom in for details.

Figure 4. Visual comparison with state-of-the-art universal methods on motion deblurring task. Please zoom in for details.

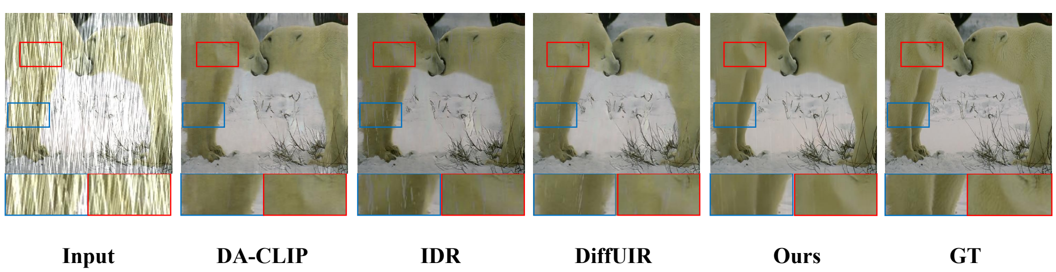

Figure 5. Visual comparison with state-of-the-art universal methods on deraining task. Please zoom in for details.

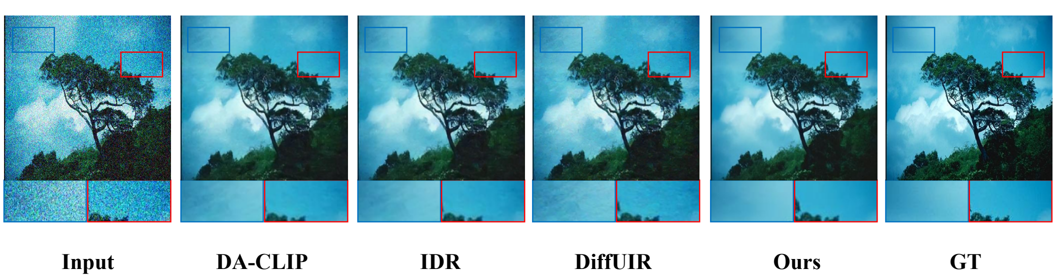

Figure 6. Visual comparison with state-of-the-art universal methods on Gaussian denoising task. Please zoom in for details.