Supplementary Material – Learning Degradation Representations for Image Deblurring

Dasong Li[1], Yi Zhang[1], Ka Chun Cheung[2], Xiaogang Wang[1,4],
Hongwei Qin[3⋆⋆], and Hongsheng Li[1,4,5⋆⋆]
[1]MMLab, CUHK [2]NVIDIA AI Technology Center [3]SenseTime Research
[4]Centre for Perceptual and Interactive Intelligence Limited [5]Xidian University
{dasongli@link, hsli@ee}.cuhk.edu.hk, qinhongwei@sensetime.com

1 Architecture of Encoder

In our framework, one encoder E and two generators G_r, G_d for reblurring and deblurring are optimized to achieve deblurring with learned degradation representations. We list the architecture and detailed operations of the encoder E in Table 1. We use leaky ReLU [2] as the activation layer. We perform the reflection padding for 1-stride convolution layers. We also add the spectral normalization [3] for all Convolution layers.

2 Ablation of Reblurring

We select our method of reblurring as the baseline and remove the 2D degradation map and adversarial training to evaluate their effectiveness. Qualitative analysis is performed on the blurry images generated from different settings. First, we replace the 2D degradation map with a 1D latent code (denoted as "G_r w/ 1D"). The results in Fig. 1 show that the 1D latent code cannot properly model the spatially varying blurry patterns. The sharp regions are also affected by the blurry regions in Fig. 1. Second, we remove the adversarial training and only use the L_1 distance as the loss function (denoted as "G_r w/ L_1 only"). It is observed in Fig. 1 that the generator G_r trained with only L_1 loss function to the ground-truth pixel values cannot well reconstruct the complicated blurry images, which affects the expressiveness of the learned degradation representations.

3 Full-frame Deblurring Results

We compare our method with HINet on GoPro [4] and RealBlur [5] test datasets for full-frame deblurring. The deblurring images for GoPro dataset and RealBlur dataset are shown in Figures 2 and 3, respectively.

[2] Corresponding authors

Fig. 1: The ablation study of image reblurring. The visual similarity between the reference and generated blurry images reflects the expressiveness of learned degradation representations.

Operation	Kernel Size	Filters	Output Size	Comments
Input	-	-	$256 \times 256 \times 3$	-
StridedConv2d	3×3	64	$128 \times 128 \times 64$	Spectral Norm
Conv2d	7×7	64	$128 \times 128 \times 64$	Reflection Padding
StridedConv2d	3×3	128	$64 \times 64 \times 128$	Spectral Norm
StridedConv2d	3×3	256	$32 \times 32 \times 256$	Spectral Norm
StridedConv2d	3×3	512	$16 \times 16 \times 512$	Spectral Norm
StridedConv2d	3×3	512	$8 \times 8 \times 512$	Spectral Norm
Conv2d	3×3	512	$8 \times 8 \times 512$	Spectral Norm
ResBlock	(3×3) - (3×3)	512 - 512	$8 \times 8 \times 512$	Reflection Padding
ResBlock	(3×3) - (3×3)	512 - 512	$8 \times 8 \times 512$	Reflection Padding
ResBlock	(3×3) - (3×3)	512 - 512	$8 \times 8 \times 512$	Reflection Padding
AvgPool2d	-	512	$4 \times 4 \times 512$	-
ResBlock	(3×3) - (3×3)	512 - 512	$4 \times 4 \times 512$	Reflection Padding
ResBlock	(3×3) - (3×3)	512 - 512	$4 \times 4 \times 512$	Reflection Padding
Conv2d	3×3	256	$4 \times 4 \times 256$	Spectral Norm + Reflection Padding

Table 1: The architecture of the encoder E.

Blurry | Reference | HINet [1] | Ours | Blurry | Reference | HINet [1] | Ours

Fig. 2: Image deblurring comparisons on the GoPro dataset [4].

Fig. 3: Image deblurring comparisons on the RealBlur dataset [5].

References

1. Chen, L., Lu, X., Zhang, J., Chu, X., Chen, C.: Hinet: Half instance normalization network for image restoration. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR) Workshops. pp. 182–192 (June 2021)
2. Maas, A.L., Hannun, A.Y., Ng, A.Y.: Rectifier nonlinearities improve neural network acoustic models. In: in ICML Workshop on Deep Learning for Audio, Speech and Language Processing (2013)
3. Miyato, T., Kataoka, T., Koyama, M., Yoshida, Y.: Spectral normalization for generative adversarial networks. In: International Conference on Learning Representations (2018), `https://openreview.net/forum?id=B1QRgziT-`
4. Nah, S., Kim, T.H., Lee, K.M.: Deep multi-scale convolutional neural network for dynamic scene deblurring. In: The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (July 2017)
5. Rim, J., Lee, H., Won, J., Cho, S.: Real-world blur dataset for learning and benchmarking deblurring algorithms. In: ECCV (25). Lecture Notes in Computer Science, vol. 12370, pp. 184–201. Springer (2020)