Supplementary for Flow-based Kernel Prior with Application to Blind Super-Resolution

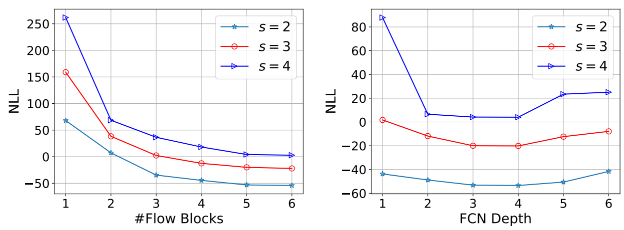
Jingyun Liang[1] Kai Zhang[1,*] Shuhang Gu[1,2] Luc Van Gool[1,3] Radu Timofte[1]

[1] Computer Vision Lab, ETH Zurich, Switzerland

[2] The University of Sydney, Australia [3] KU Leuven, Belgium

{jinliang, kai.zhang, vangool, timofter}@vision.ee.ethz.ch shuhanggu@gmail.com

https://github.com/JingyunLiang/FKP



(a) (b)

Figure 1: The effects of different numbers of flow blocks and FCN depths on negative log-likelihood (NLL) of kernels.

1. Ablation Study on FKP

To evaluate the effects of the total number of flow blocks and fully-connected network (FCN) depths in FKP, we generate a testing set by sampling kernels with a kernel width step of 0.3 and rotation angle step of 0.2. We compare different parameter settings by the average NLL of the last epoch on the testing set as the NLL loss used in training reflects the kernel modeling likelihood. It can be observed from Fig. 1(a) that NLL has a decreasing tendency with the number of flow blocks, indicating that more flow blocks generally improve the modeling ability of FKP. From Fig. 1(b), one can see that too shallow or too deep FCN lead to performance drop, maybe due to under-fitting or overfitting, respectively. As a result, to balance kernel modeling performance and computation cost, we use 5 flow blocks and 3 fully-connected layers in FKP.

2. Kernel Estimation Under Ideal Circumstance

As a kernel prior, FKP can generate a kernel under the guidance of kernel estimation loss functions. To show how FKP works, we use the mean absolute error (MAE) between kernel estimation and the ground-truth as an ideal kernel estimation loss. As shown in Figure 2, FKP converges quickly and is able to generate kernels accurately in 20 iterations even though the kernel initialization is far from the ground-truth. When we optimize it for more iterations, there are further improvements in accuracy. It is noteworthy that, in this specific case, we can also input the ground-truth kernel into FKP in order to obtain the corresponding latent variable as FKP is a bijection, though it is not applicable in the kernel estimation problem.

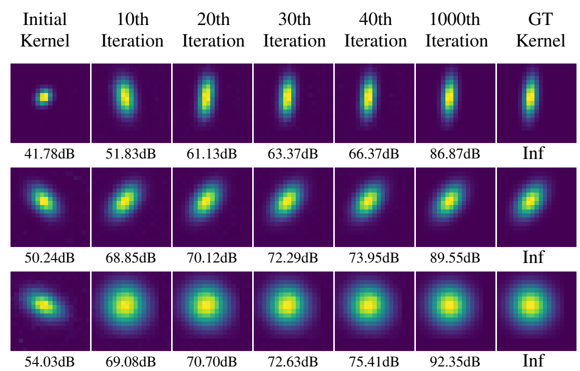


Figure 2: The intermediate results of kernel estimation under the guidance of an ideal kernel reconstruction loss. The PSNR of kernel is shown below each kernel estimation.

3. More Visual Comparisons

We provide more visual comparisons to show the superiority of the proposed DIP-FKP and KernelGAN-FKP, as shown in Fig. 3 and Fig. 4.

References

[1] Yossi Gandelsman, Assaf Shocher, and Michal Irani. Double-dip": Unsupervised image decomposition via coupled deep-

*Corresponding author.

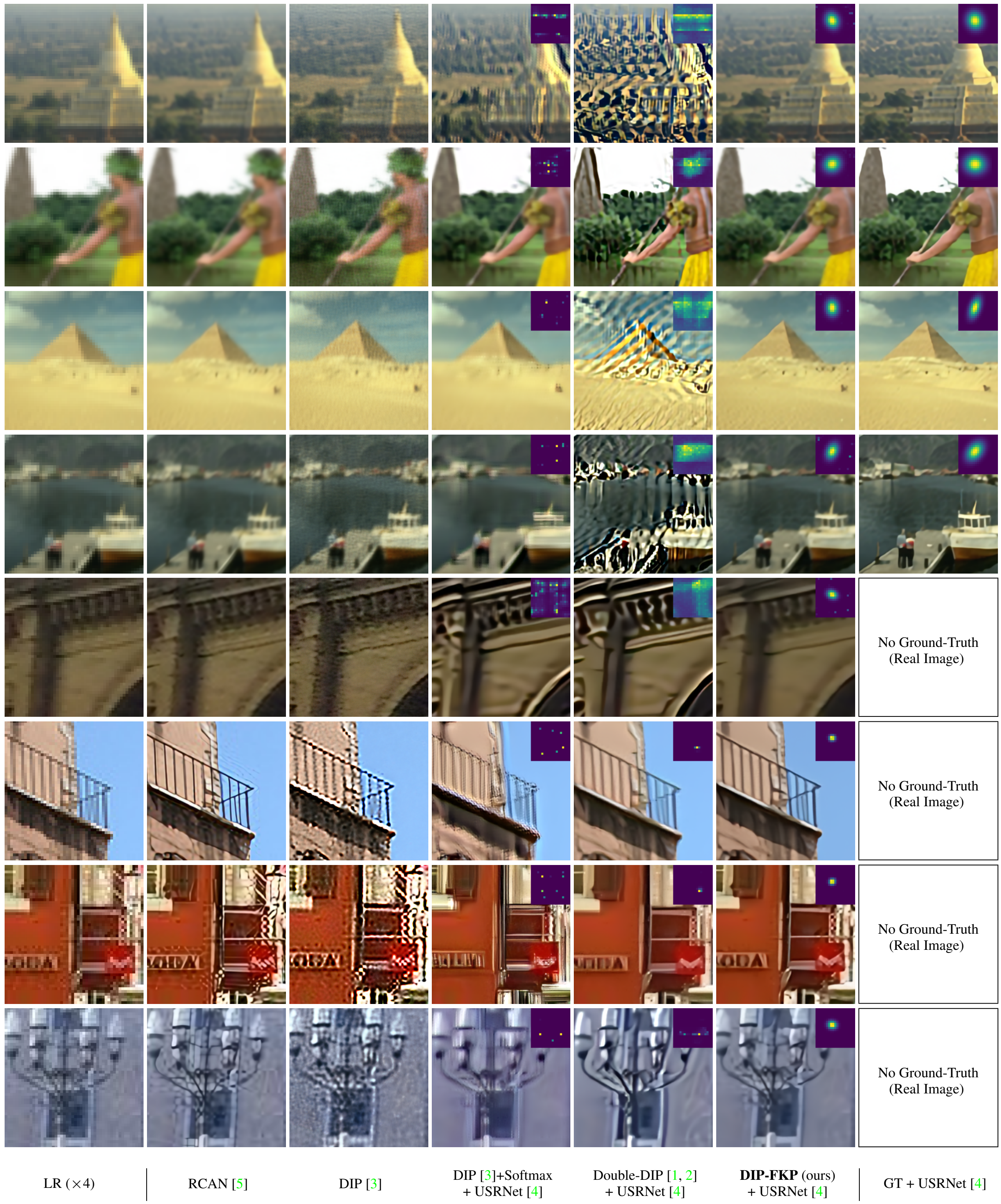


Figure 3: More visual results of different methods on synthetic and real-world images for scale factor 4. Estimated/ground-truth kernels are shown on the top right of images.

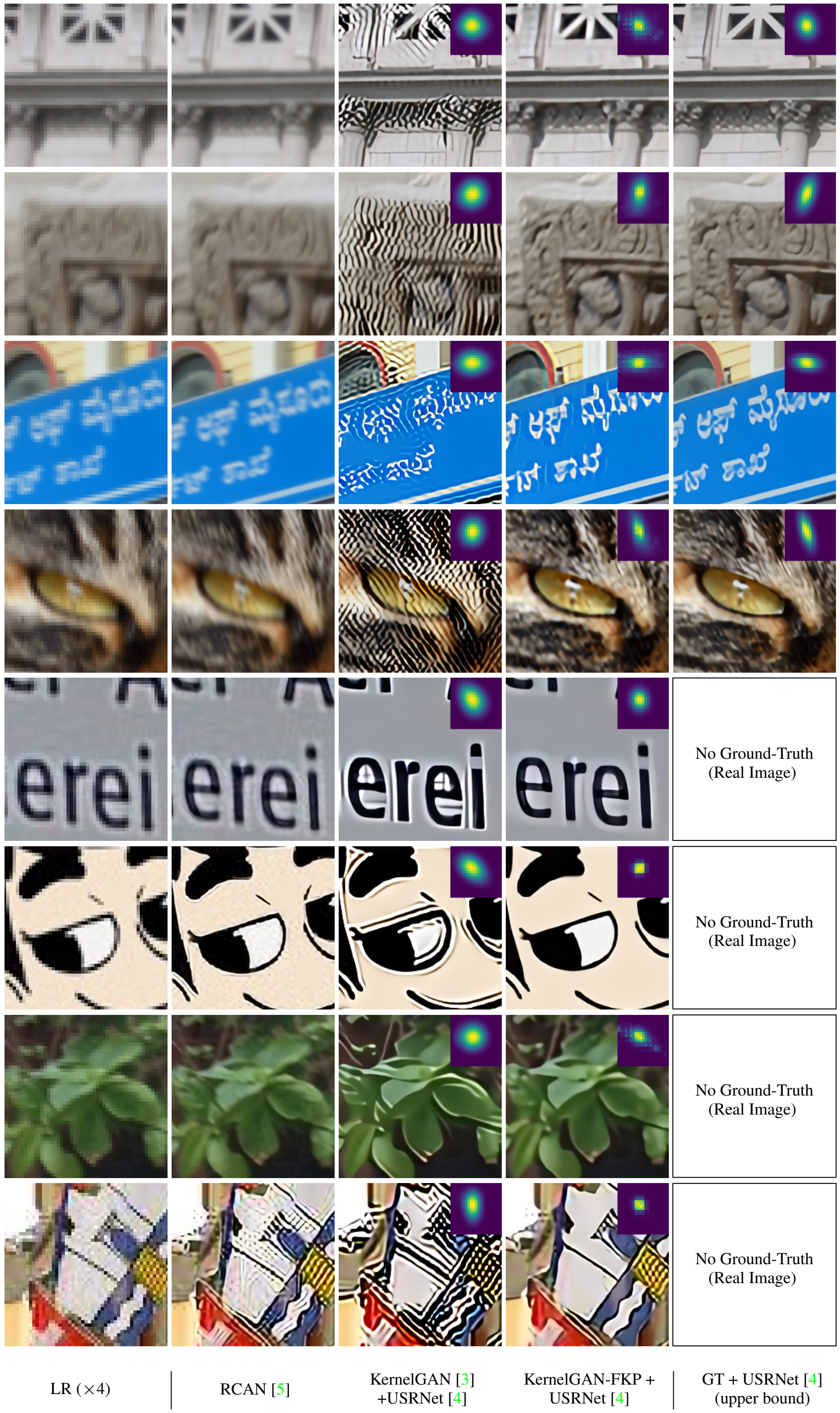


Figure 4: More visual results of different methods on synthetic and real-world images for scale factor 4. Estimated/ground-truth kernels are shown on the top right of images.

image-priors. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 11026–11035, 2019. 2

[2] Dongwei Ren, Kai Zhang, Qilong Wang, Qinghua Hu, and Wangmeng Zuo. Neural blind deconvolution using deep priors. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 3341–3350, 2020. 2

[3] Dmitry Ulyanov, Andrea Vedaldi, and Victor Lempitsky. Deep image prior. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 9446–9454, 2018. 2, 3

[4] Kai Zhang, Luc Van Gool, and Radu Timofte. Deep unfolding network for image super-resolution. In *IEEE Conference on Computer Vision and Pattern Recognition*, pages 3217–3226, 2020. 2, 3

[5] Yulun Zhang, Kunpeng Li, Kai Li, Lichen Wang, Bineng Zhong, and Yun Fu. Image super-resolution using very deep residual channel attention networks. In *European Conference on Computer Vision*, pages 286–301, 2018. 2, 3