Supplementary material - NSSR-DIL: Null-Shot Image Super-Resolution Using Deep Identity Learning

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1 Ablation study

In this section, the performance of the NSSR-DIL method for various sizes of the RKG dataset, and on unseen synthetic test dataset were quantified and discussed.

1.1 Image Super-Resolution of scale factors $> \times 4$

The existing SotA ISR works are limited to performing the ISR task for scale factors up to 4, especially the zero-shot approaches. The present zero-shot approaches are restricted by their assumption in the ISR task definition i.e. patch recurrence property across the scales of the image, to extend for sfs beyond $\times 4$ [1, 2] etc. Additionally, the existing SotA ISR methods based on deep models are bound to increase the computational complexity in terms of memory and time to achieve sfs above $\times 4$.

In this work, the proposed NSSR-DIL model can be easily extended to any higher scale factors like $\times 16$ & $\times 32$ without an increase in computational footprint. The performance of the proposed NSSR-DIL model was found satisfactory when compared to traditional interpolation methods like Bicubic interpolation, which can also be extended to any sfs. It is crucial to note that, in the case of NSSR-DIL, the number of parameters remains the same irrespective of varying sf.
In our experiments, the HR ground-truth images in the DIV2KRK dataset were considered to generate the LR images of $\times 8, \times 16, \times 32$. The anisotropic gaussian kernels having $\sigma_1, \sigma_2 \in U[0.175, 3.1]$ and rotation angle $\theta \in U[0, \pi]$ with dimensions $31 \times 31, 41 \times 41, 51 \times 51$ were used to generate the LR images of sf $\times 8, \times 16, \times 32$ respectively. The results were tabulated in Table no. 1. It was observed that the proposed method superseded the standard Bicubic interpolation method in terms of SSIM for higher sfs.

1.2 Performance of NSSR-DIL on unseen synthetic dataset

We have prepared a synthetic test dataset with the degradation kernels outside of our training dataset. We used the DIV2K validation set to generate LR images using random Gaussian

Table 1: Comparison of ISR performance of higher scale factors using SSIM↑/PSNR↑ metrics.

Scale factor	**Bicubic**	**NSSR-DIL (Ours)**
x2	0.7846/27.24	0.8644/26.02
x4	0.6478/23.89	0.7926/23.58
x8	0.6250/23.31	0.7625/23.35
x16	0.5666/21.33	0.7132/21.34
x32	0.5348/19.34	0.6713/19.25

kernels with size 11×11 and 21×21 of varying shapes, and orientations i.e. $\sigma_1, \sigma_2 \in U[3,5]$ and rotation angle $\theta \in U[0,\pi]$ for scale factor 2 and 4 respectively. These random Gaussian kernels are further perturbed by uniform multiplicative noise as well. The model's performance results on this synthetic ISR dataset in Table 2 demonstrate the robustness of the proposed NSSR on unseen degradations.

Table 2: ISR performance of the proposed NSSR-DIL on the synthetic dataset generated using the unseen kernels in terms of SSIM↑, NIMA↑, and PSNR↑ were given below

	Scale factor	**SSIM**	**NIMA**	**PSNR**
NSSR-DIL	X2	0.8257	4.94	24.79
	X4	0.7741	4.88	23.25

1.3 Performance of NSSR-DIL with varied sizes of RKG dataset

We studied the performance of the NSSR-DIL model trained on varied sizes of the RKG dataset. In our study, we generated five different datasets with the number of samples $800, 1600, 2400, 3200, 4000$, and 4800 and named as RKG_n, where $n = 1,2,3,4,5$, respectively. These five datasets i.e. RKG_n were generated following the steps discussed in Sec. 3.2. The L-CNN was trained independently on each set and evaluated on the DIV2KRK test dataset for sf 2. The visual plots depicting the L-CNN performance comparison for RKG_n vs evaluation metrics i.e. NIMA, SSIM, and PSNR are presented in Fig. 1. It is observed that there is a linear improvement in these metrics as the number of samples was increased initially and saturated later. Therefore we considered 3200 training samples i.e., RKG_4 dataset in all our experiments.

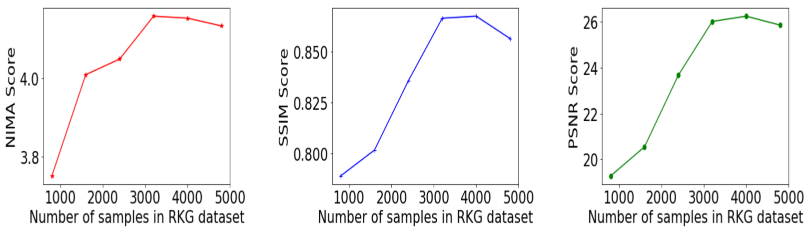

Figure 1: The performance comparison of the NSSR-DIL model with sizes of RKG dataset.

References

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