Supplementary for Image Super-Resolution with Deep Dictionary

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1 More Training Details

Learning rate Different learning rates are employed for the high-resolution dictionary D_{H} and the rest of the network. When D_{H} was trained at the same low learning rate as the others, the atoms remained in their initial state and were hardly updated.

Augmentations Following previous studies, random flipping and rotation augmentation is applied to each training sample. We also tried color augmentations of blend and RGB permute [1]; however, performance did not improve.

Validation Initial ten images from the DIV2K validation dataset are used for validation. To reduce the validation cost, a 256×256 (128×128) region of each image is cropped to input the $\times 4$ ($\times 8$) model. The weight that maximizes the validation score was used for all evaluations.

Residual learning In SRDD, it is important to learn residuals from upsampled input images. Attempting to reconstruct the image directly instead of learning the residuals made the training unstable and resulted in significant performance degradation.

Evolution of atoms Figure 1 shows evolution of atoms during training. We observed that the contrast of the output atoms became stronger as training progressed, and they were almost fixed in the latter half of the training.

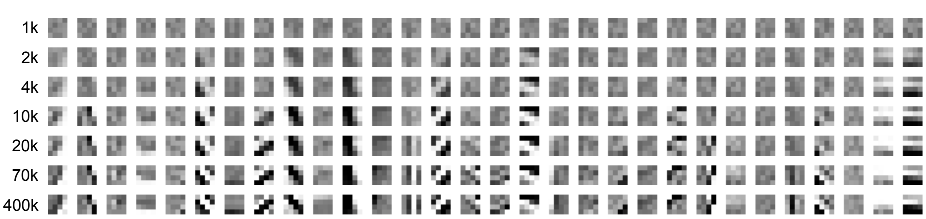

Fig. 1. Evolution of atoms during training of $\times 4$ SRDD with $N = 64$. The 30 atoms under the training from 1k to 400k iterations are displayed. The data range is renormalized to $[0, 1]$ for visualization.

References

1. Yoo, J., Ahn, N., Sohn, K.A.: Rethinking data augmentation for image super-resolution: A comprehensive analysis and a new strategy. In: CVPR (2020)