Meta-Transfer Learning for Zero-Shot Super-Resolution - Supplementary Material

Jae Woong Soh  Sunwoo Cho  Nam Ik Cho
Department of ECE, INMC, Seoul National University, Seoul, Korea
{soh90815, etoo33}@ispl.snu.ac.kr, nicho@snu.ac.kr

1. Evaluation on Scaling Factor $\times 4$

To evaluate the performance on large scaling factors, we demonstrate the results on scaling factor $\times 4$ with isotropic Gaussian kernel with width 2.0 in Table 1. As shown, our methods show comparable results to others even with one gradient update, for large scaling factors too. Also, we found that multi-scale model shows worse results than a single-scale model as evidenced in the scaling factor $\times 2$.

2. Effects of Kernels on Meta-test Time

To evaluate the effects of input kernels on meta-test time, we obtained several results by feeding various kernels. The results are shown in Figure 1. It is obvious that kernel mismatch degrades the output result severely. Especially, when the input kernel largely deviates from the true kernel, the result is not very pleasing as shown in Figure 1(a) and (b). However, if the input kernel has similar shape as the true kernel then the result looks quite plausible as shown in Figure 1(c). In conclusion, the kernel estimation or knowing the true kernel is crucial for the performance gain with our method.

3. Visualization

To show the effectiveness of our MZSR, we visualize some results including scenarios with synthetic blur kernels and real-world images. Figure 2, 3, and 4 are the results on synthetic blur kernels. Figure 5, 6, and 7 are the results on real-world images.

References

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Table 1: Average PSNR/SSIM results on the scaling factor $\times 4$ on benchmarks. The numbers in parenthesis in our methods stand for the number of gradient updates. The best and the second best are highlighted in red and blue, respectively.

![Table 1](image)

Figure 1: Comparisons when different kernels are applied on meta-test time. The last result is when the true kernel is applied.

![Figure 1](image)

Figure 2: Visualized comparisons of super-resolution results ($\times 2$) with anisotropic blur kernel $g_{ani}^d$.  

![Figure 2](image)
Figure 3: Visualized comparisons of super-resolution results ($\times 2$) with aliasing degradation $g_{0.2}^d$.

Figure 4: Visualized comparisons of super-resolution results ($\times 2$) with isotropic blur kernel and bicubic subsampling $g_{1.3}^b$. 
Figure 5: Visualized comparisons of super-resolution results (×4) on real-world image.

Figure 6: Visualized comparisons of super-resolution results (×4) on real-world image.
Figure 7: Visualized comparisons of super-resolution results (×4) on historic image.