

# Supplementary Material for "Deep Degradation Prior for Real-World Super-Resolution"

Kyungdeuk Ko<sup>1</sup>  
kdko@korea.ac.kr

Bokyeung Lee<sup>1</sup>  
bksain@korea.ac.kr

Jonghwan Hong<sup>1</sup>  
jhong2661@korea.ac.kr

David Han<sup>2</sup>  
dkh42@drexel.edu

Hanseok Ko<sup>1</sup>  
hsko@korea.ac.kr

<sup>1</sup> Korea University  
Seoul, Republic of Korea

<sup>2</sup> Drexel University  
Philadelphia, USA

## 1 Supplementary Material

In this supplementary material, we describes additional contents of 4. Experiment section in main manuscript.

### 1.1 Additional Results on DPED

Figure 1 displays additional qualitative results on DPED [5] dataset. SRMD[6], IKC[7], ZSSR [8], K-ZSSR combined with ZSSR and KernelGAN [9], and RealSR [10] are used as baseline methods. In the Figure 1, we can check that SRMD, IKC and ZSSR make blur images. K-ZSSR generates unexplainable artifacts, and the results of RealSR have over-sharpening. On the other hand, our proposed method reduces artifacts and over-sharpening.

### 1.2 Additional Results on Generalization

Figure 2 shows additional qualitative results on RealSR-V3 dataset [11] dataset, and Figure 3 shows additional qualitative results on DIV2K dataset [12] and CelebA-HQ dataset [13]. To demonstrate generalization performance of our proposed method, we present the results obtained by testing with the RealSR-V3, DIV2K, and CelebA-HQ on the network trained with the DPED dataset. The RealSR reconstructs unrecognizable letters, unnatural patterns, and darker images than the GT. On the other hand, our proposed method provides better structural information, clear letters, and brightness similar to the GT. As a result, our proposed method accomplishes high generalization performance.

### 1.3 Qualitative Results on Ablation Study

Figure 4 exhibits the qualitative results on 4.3 Ablation Study section in the main manuscript. One experiment is conducted when only one of the deep noise prior and the deep kernel prior is applied. Another experiment is conducted depending on where the deep noise prior and the deep kernel prior are applied in RDB [14]. The other experiment is conducted depending on the layer where the deep noise prior is extracted from the deep noise prior generator. The results of other architectures have over-sharpened edge and lack of details in the pattern. In Figure 4, our proposed architecture represents the better details of the tree branches and reduces over-sharpening in the letters.



Figure 1: Additional results on the DPED dataset

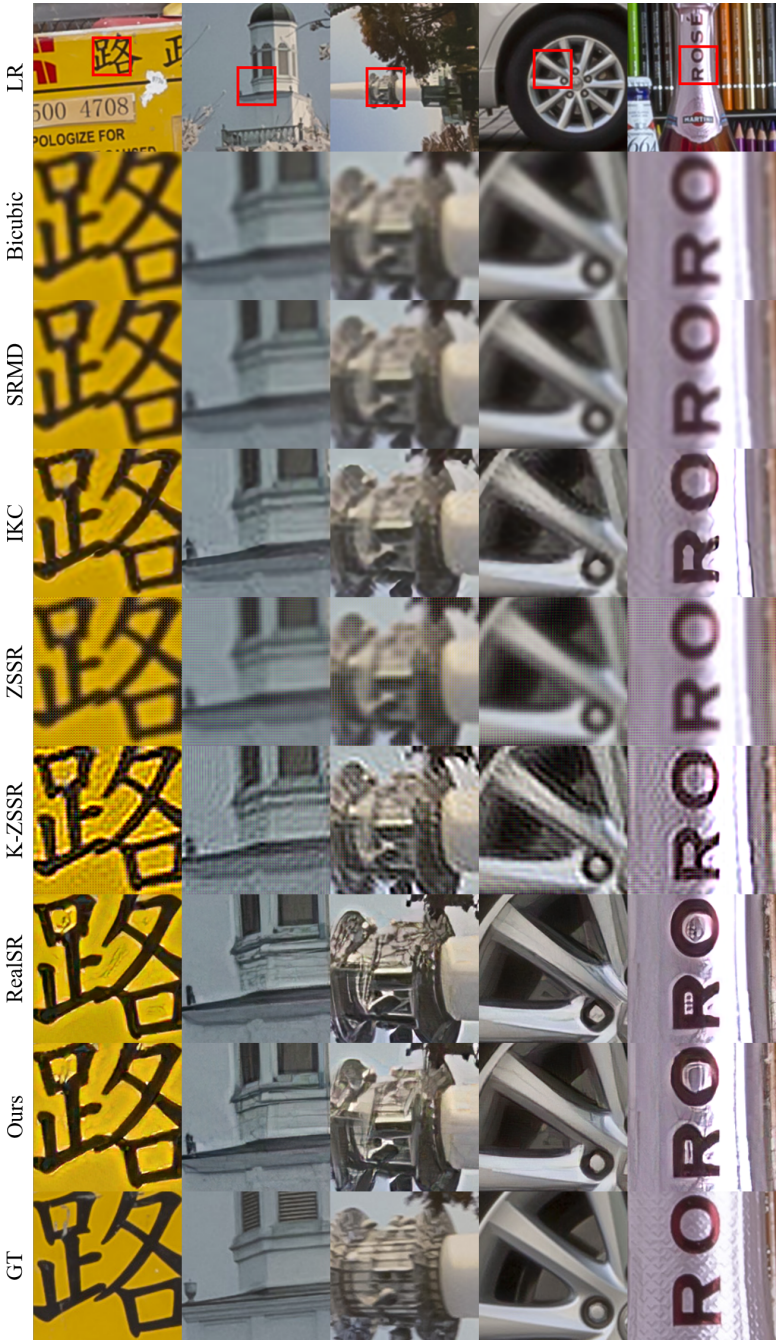


Figure 2: Additional results on the RealSR-V3 dataset





Figure 3: Additional results on the DIV2K dataset and CelebA-HQ



Figure 4: Qualitative results on the ablation study

## References

- [1] Eirikur Agustsson and Radu Timofte. Ntire 2017 challenge on single image super-resolution: Dataset and study. In *Proceedings of the IEEE conference on computer vision and pattern recognition workshops*, pages 126–135, 2017.
- [2] Sefi Bell-Kligler, Assaf Shocher, and Michal Irani. Blind super-resolution kernel estimation using an internal-gan. *arXiv preprint arXiv:1909.06581*, 2019.
- [3] Jianrui Cai, Hui Zeng, Hongwei Yong, Zisheng Cao, and Lei Zhang. Toward real-world single image super-resolution: A new benchmark and a new model. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 3086–3095, 2019.
- [4] Jinjin Gu, Hannan Lu, Wangmeng Zuo, and Chao Dong. Blind super-resolution with iterative kernel correction. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 1604–1613, 2019.
- [5] Andrey Ignatov, Nikolay Kobyshev, Radu Timofte, Kenneth Vanhoey, and Luc Van Gool. Dslr-quality photos on mobile devices with deep convolutional networks. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 3277–3285, 2017.
- [6] Xiaozhong Ji, Yun Cao, Ying Tai, Chengjie Wang, Jilin Li, and Feiyue Huang. Real-world super-resolution via kernel estimation and noise injection. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops*, pages 466–467, 2020.
- [7] Tero Karras, Timo Aila, Samuli Laine, and Jaakko Lehtinen. Progressive growing of gans for improved quality, stability, and variation. *arXiv preprint arXiv:1710.10196*, 2017.
- [8] Assaf Shocher, Nadav Cohen, and Michal Irani. “zero-shot” super-resolution using deep internal learning. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 3118–3126, 2018.
- [9] Kai Zhang, Wangmeng Zuo, and Lei Zhang. Learning a single convolutional super-resolution network for multiple degradations. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 3262–3271, 2018.
- [10] Yulun Zhang, Yapeng Tian, Yu Kong, Bineng Zhong, and Yun Fu. Residual dense network for image super-resolution. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 2472–2481, 2018.