

Supplementary Materials to “Degradation Model Learning for Real-World Single Image Super-resolution”

Jin Xiao¹, Hongwei Yong^{1,2}, and Lei Zhang^{1,2*}

¹ Department of Computing, The Hong Kong Polytechnic University, Hong Kong

² DAMO Academy, Alibaba Group, Hangzhou, China

{csjxiao, cshyong, cslzhang}@comp.polyu.edu.hk

In this supplementary file, we provide the following materials:

1. Visual comparison of competing SISR models on the RealSR [1] dataset;
2. Visual comparison of competing SISR models on the SR-RGB [2] dataset.

We compare the SISR results of VDSR/RCAN models trained on different training datasets, i.e., only RealSR [1], only Syn-DSGAN [3], only Syn-DML, the combination of RealSR and Syn-DSGAN, and the combination of RealSR and Syn-DML (please refer to Section 4.4 in the main paper).

1 Visual comparison of competing SISR models on the RealSR [1] dataset.

Fig. 1 ~ Fig. 3 show the super-resolved images from the RealSR [1] dataset with zooming factors $\times 2$, $\times 3$ and $\times 4$, respectively. One can see that models trained on Syn-DSGAN produce noticeable artifacts. Models trained on Syn-DML can effectively recover more image details with more pleasant perceptual quality than those trained using only the RealSR dataset. The models trained on RealSR+Syn-DML achieve the best visual quality.

2 Visual comparison of competing SISR models on the SR-RGB [2] dataset.

Fig. 4 ~ Fig. 6 show the super-resolved images from the SR-RGB [2] dataset with zooming factors $\times 2$, $\times 3$ and $\times 4$, respectively. One can observe that models trained on the RealSR dataset can only moderately recover some details. Models trained on Syn-DSGAN produce severe artifacts. Benefitting from the enlarged realistic training data, SISR models trained on Syn-DML dataset can produce visually pleasing results with more fine-grained details. And the models trained on combined RealSR+Syn-DML deliver the best perceptual quality of super-resolved HR images. This demonstrates that our proposed degradation model learning method can effectively improve the generalization performance of SISR models to real-world applications.

* Corresponding author. This work is supported by the Hong Kong RGC GRF grant (PolyU 152216/18E).

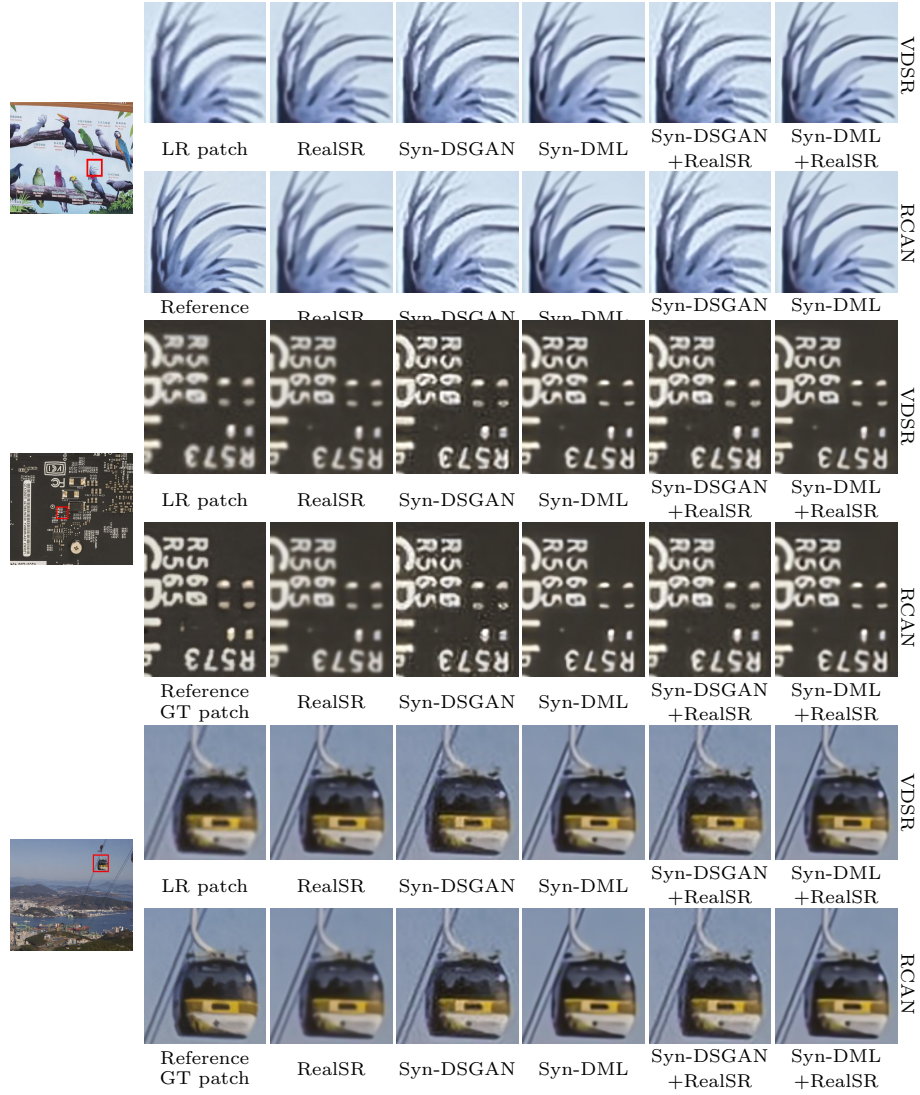


Fig. 1. Visual comparison of the competing SISR models on RealSR [1] dataset with zooming factor $\times 2$. The first and second rows of each example are super-resolved patches by VDSR and RCAN networks, respectively, which are trained using different training data.



Fig. 2. Visual comparison of the competing SISR models on RealSR [1] dataset with zooming factor $\times 3$. The first and second rows of each example are super-resolved patches by VDSR and RCAN networks, respectively, which are trained using different training data.

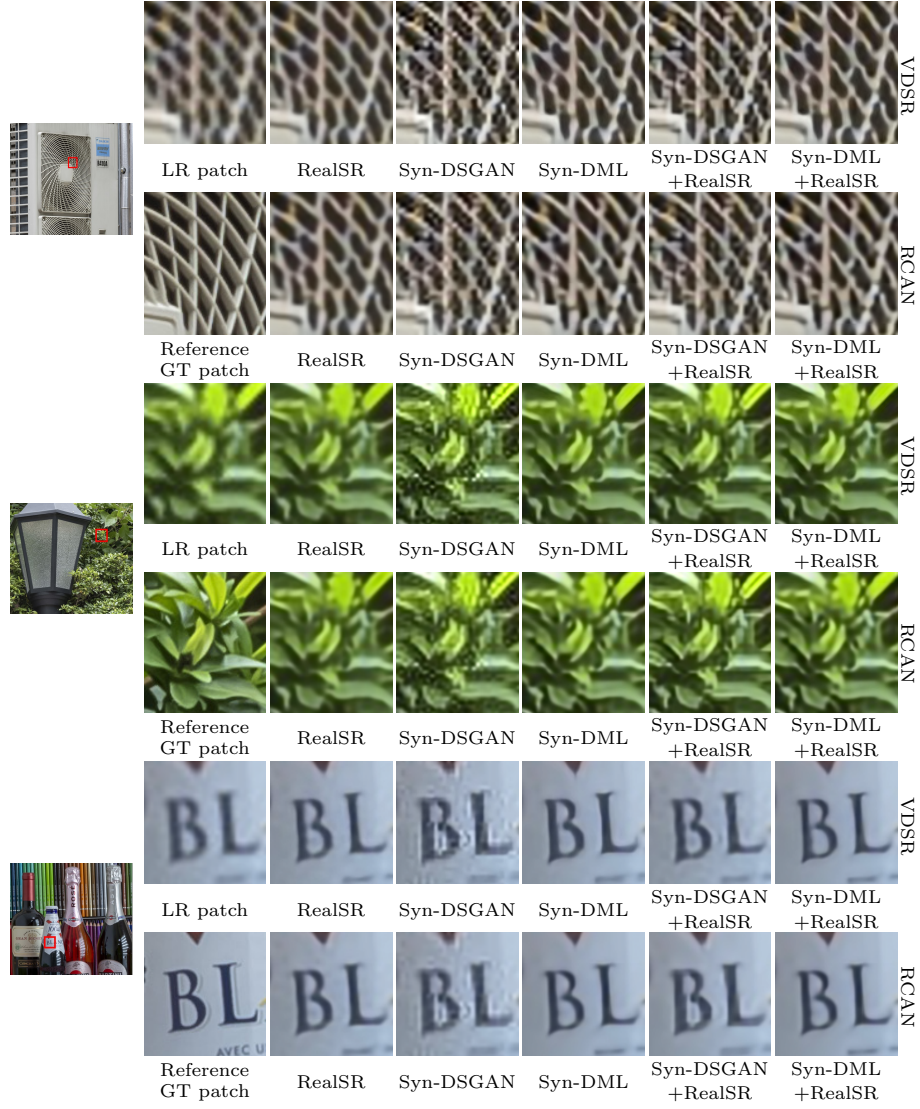


Fig. 3. Visual comparison of the competing SISR models on RealSR [1] dataset with zooming factor $\times 4$. The first and second rows of each example are super-resolved patches by VDSR and RCAN networks, respectively, which are trained using different training data.

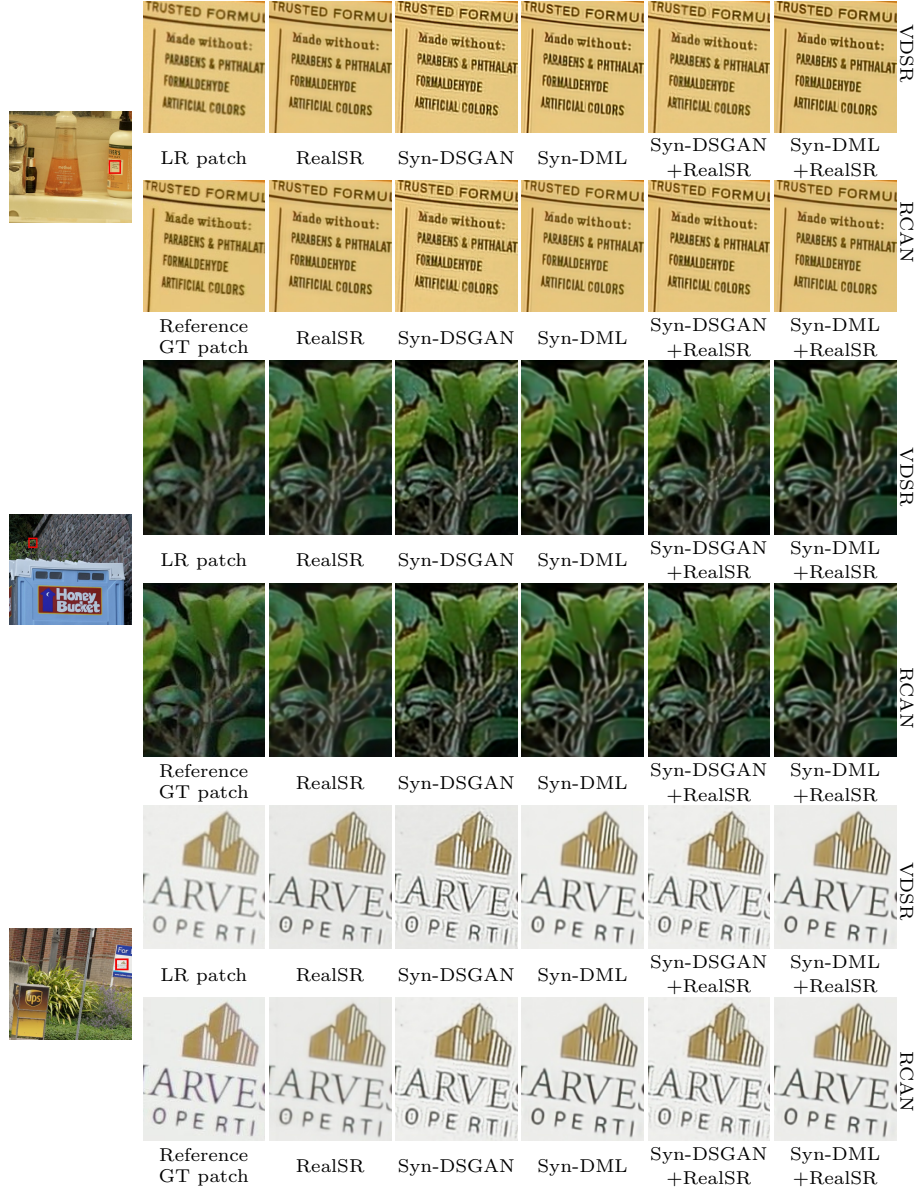


Fig. 4. Visual comparison of the competing SISR models on SR-RGB [2] dataset with zooming factor $\times 2$. The first and second rows of each example are super-resolved patches by VDSR and RCAN networks, respectively, which are trained using different training data.

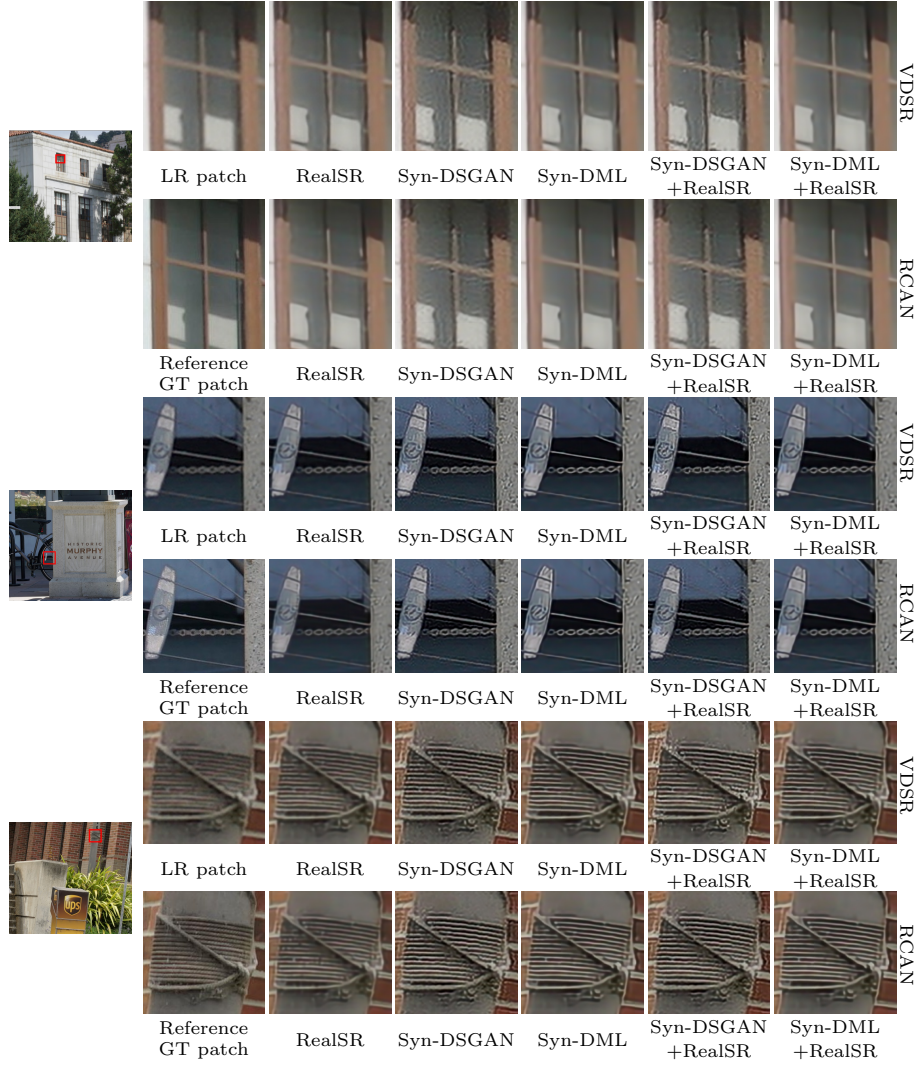


Fig. 5. Visual comparison of the competing SISR models on SR-RGB [2] dataset with zooming factor $\times 3$. The first and second rows of each example are super-resolved patches by VDSR and RCAN networks, respectively, which are trained using different training data.

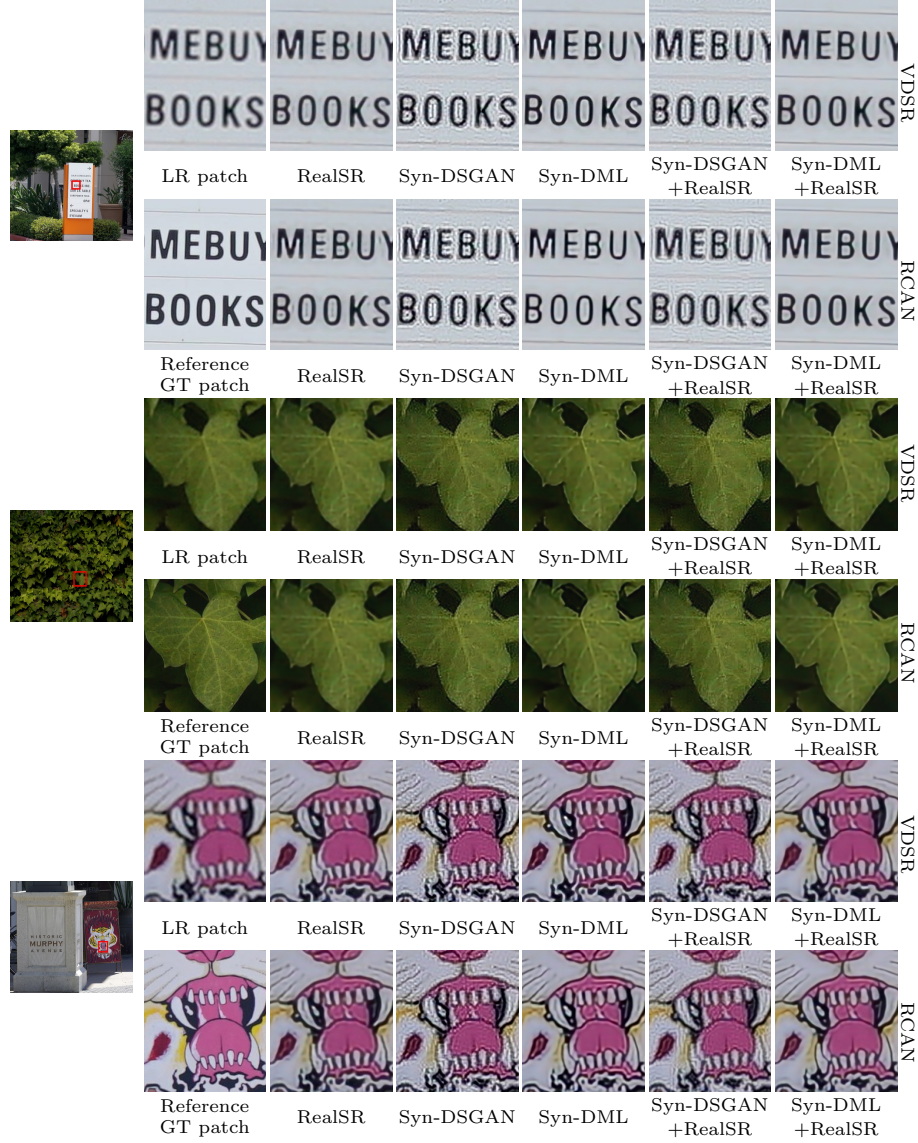


Fig. 6. Visual comparison of the competing SISR models on SR-RGB [2] dataset with zooming factor $\times 4$. The first and second rows of each example are super-resolved patches by VDSR and RCAN networks, respectively, which are trained using different training data.

References

1. Cai, J., Zeng, H., Yong, H., Cao, Z., Zhang, L.: Toward real-world single image super-resolution: A new benchmark and a new model. In: Proceedings of the IEEE International Conference on Computer Vision. (2019) 3086–3095
2. Zhang, X., Chen, Q., Ng, R., Koltun, V.: Zoom to learn, learn to zoom. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. (2019) 3762–3770
3. Fritsche, M., Gu, S., Timofte, R.: Frequency separation for real-world super-resolution. arXiv preprint arXiv:1911.07850 (2019)