Texture Hallucination for Large-Scale Painting Super-Resolution

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A. Visual Comparisons

This section will demonstrate more visual comparison between the state-of-the-art methods and the proposed method on the newly collected PaintHD dataset. More specifically, our method is compared to a state-of-the-art SISR method RCAN [1] and a representative Ref-SR method SRNTT [2]. The comparison will be conducted at 8× and 16×, respectively.

A.1. Results of 8×

The visual comparison of 8× upscaling is shown in Figs. A.1 and A.2. Each example spans two rows, where the upper and lower figures in the first column are the LR input and reference, respectively. The rest columns are results from corresponding methods. For better visual comparison, only two zoom-in areas are cropped from the original results as indicated by the color-coded boxes in the LR input. The input and reference may be patches from the same original painting, but they avoid large overlap and would show different scales, angles, and styles of the stroke.

A.2. Results of 16×

By the same token, the visual comparison is conducted at 16× in the similar way as shown in Figs. A.3 and A.4.

A.3. Effect of Different References

For Ref-SR methods, investigation on the effect from references is an interesting and opening problem, *e.g.*, how the references affect SR results, how to control (*i.e.*, utilize or suppress) such effect, etc. This section intends to explore the effect of references in the proposed Ref-SR method. As shown in Figs. A.5 and A.6, the same LR input is super-resolved using different reference images, respectively.

In general, the local texture in the results would vary with the reference texture. In Fig. A.5, the stroke/texture scale in Reference 1 is relatively smaller than that in Reference 2, thus the texture presented in the results using Reference 1 would be of smaller scale, *i.e.*, more details and visually sharper. In Fig. A.6, Reference 2 shows stronger canvas texture, which is transferred to the results. The proposed method transfers the texture from different references to the results, while preserving the content of the LR input.

References

[1] Yulun Zhang, Kunpeng Li, Kai Li, Lichen Wang, Bineng Zhong, and Yun Fu. Image super-resolution using very deep residual channel attention networks. In *ECCV*, 2018. 1, 2, 3, 4, 5

[2] Zhifei Zhang, Zhaowen Wang, Zhe Lin, and Hairong Qi. Image super-resolution by neural texture transfer. In *CVPR*, 2019. 1, 2, 3, 4, 5

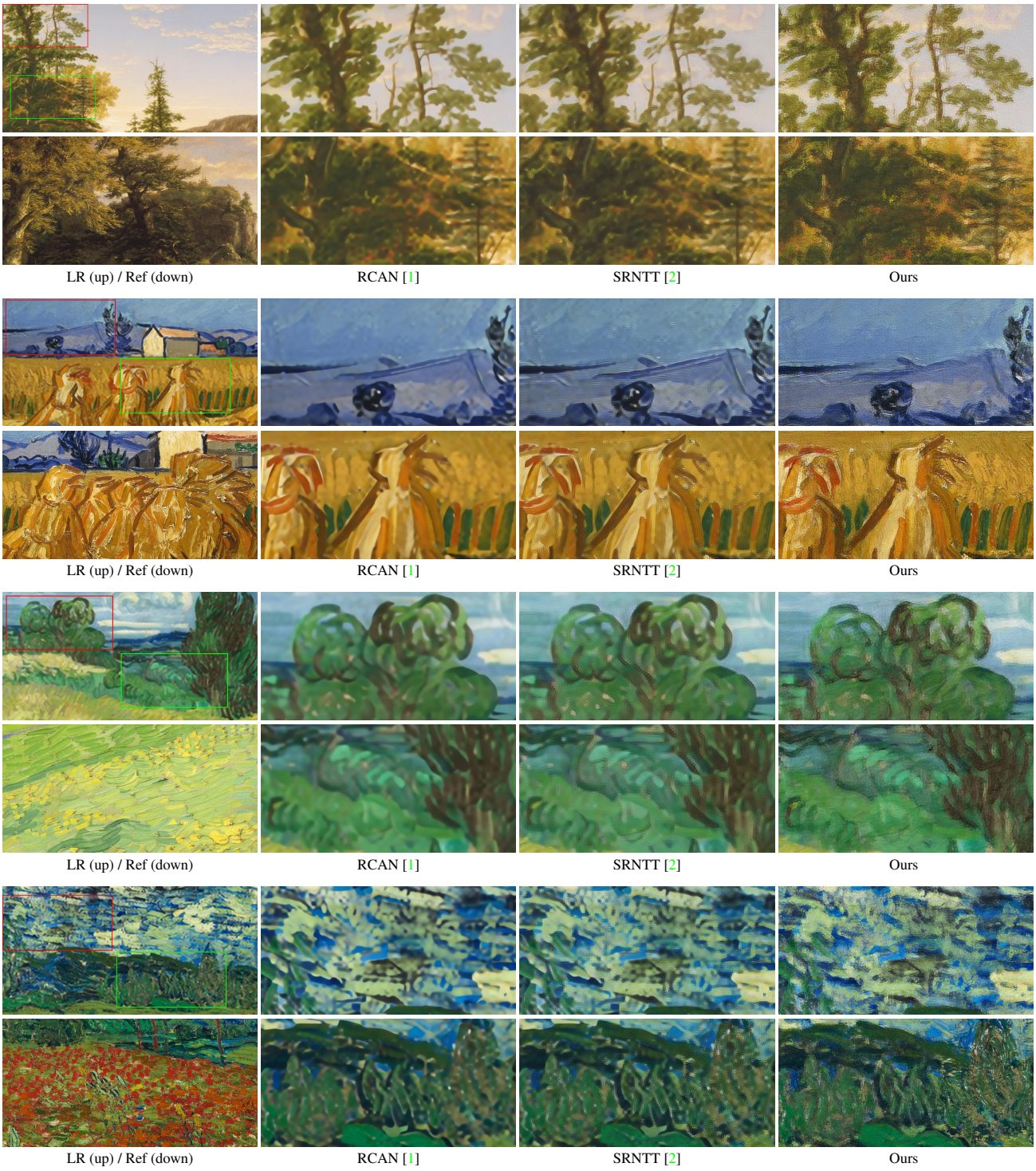

Figure A.1: Visual results with scaling factor $8\times$.

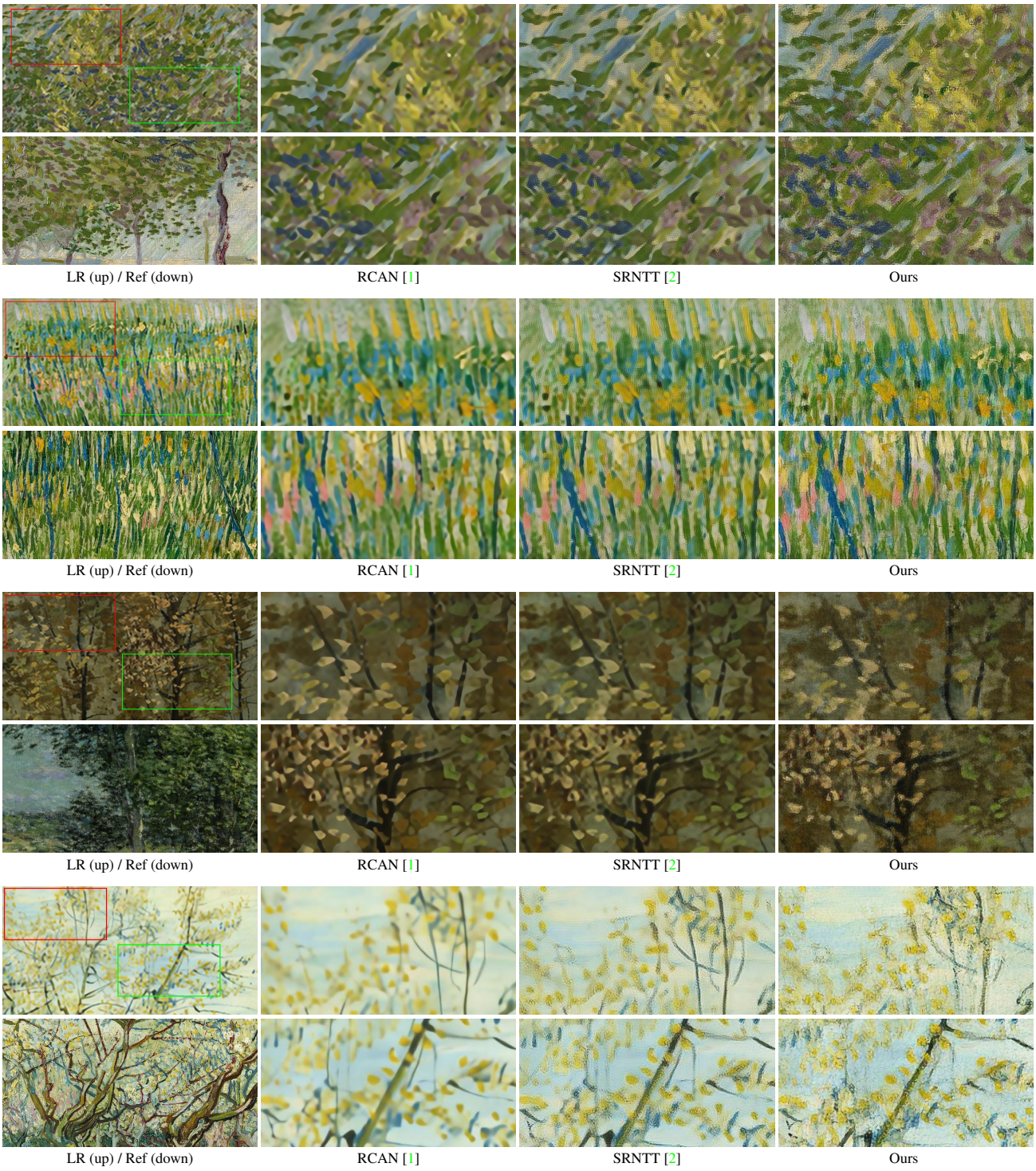

Figure A.2: Visual results with scaling factor $8\times$.

Figure A.3: Visual results with scaling factor $16\times$.

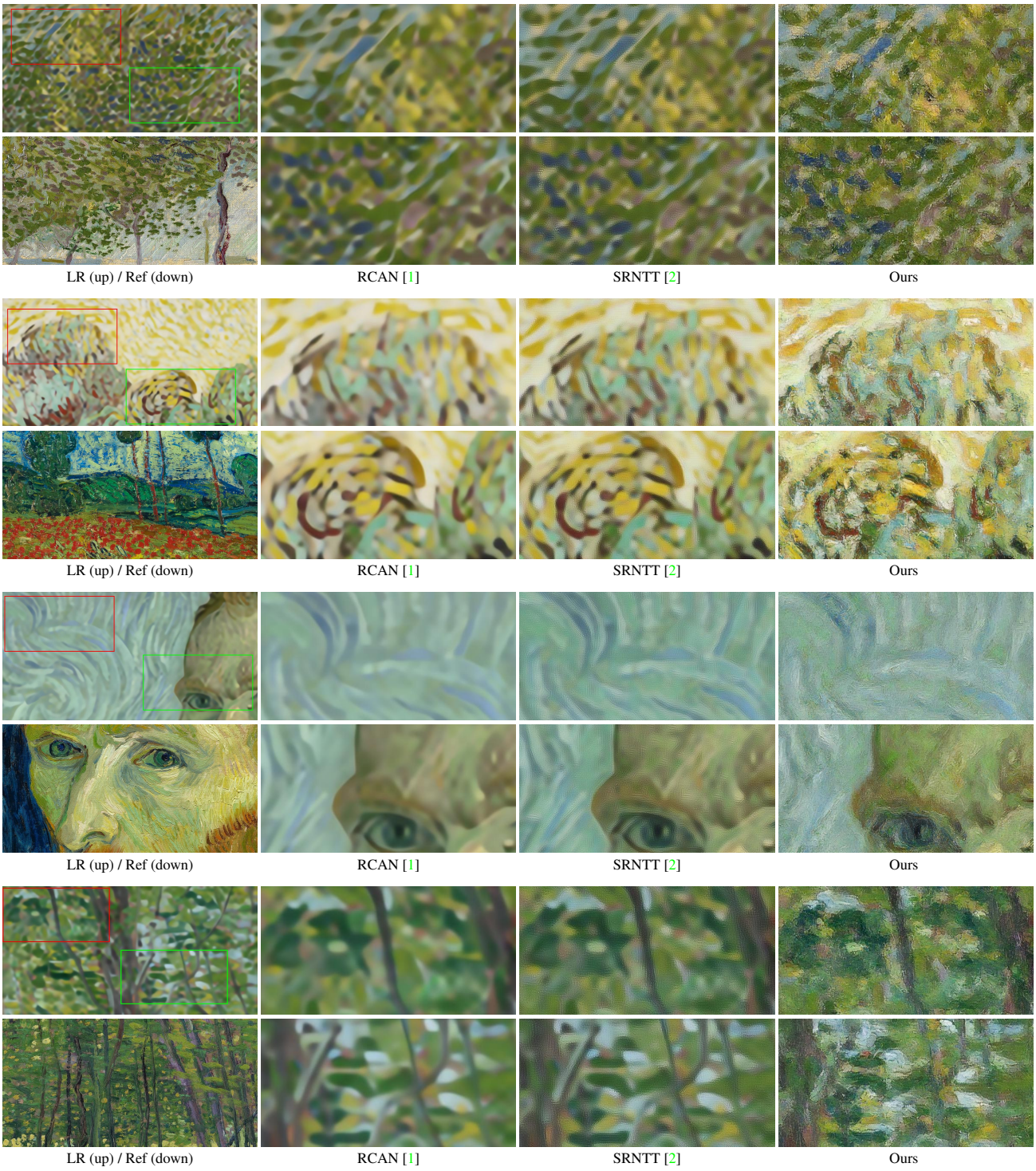

Figure A.4: Visual results with scaling factor $16\times$.

Figure A.5: Visual results with scaling factor $8\times$ using different reference images. For each reference image, we show three patches extracted from the corresponding results.

Figure A.6: Visual results with scaling factor $8\times$ using different reference images. For each reference image, we show three patches extracted from the corresponding results.