Supplementary Materials for "Downscaled Representation Matters: Improving Image Rescaling with Collaborative Downscaled Images"

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In the main paper, we propose a Hierarchical Collaborative Downscaling (HCD) scheme that optimizes the representations in both HR and LR domains to obtain a better downscaled example. In this supplementary material, we will provide more visualization results. The supplementary materials are organized as follows:

- Appendix A: We provide more visualization results of the collaborative LR examples and the corresponding generated perturbations. The results show that the generated collaborative examples can provide more high-frequency information which are often hard to be reconstructed in the upscaling process.
- Appendix B: We report more visual comparison results of reconstructed images. The results show HR images reconstructed by HCD achieve better visual quality and fidelity than the previous SOTA methods.
- Appendix C: We show the visualization images of our collaborative downscaled images and bicubic LR images. The results indicate that images downscaled by HCD have similar visual perceptions to images downscaled by bicubic.

A. Visualization of Perturbations

Following [3], we perturbate in the HR image and LR image domains to obtain better downsampled representations. As shown in Figure I, we put more generated collaborative downscaled images and the corresponding generated perturbations in this section. The visualization results show that perturbations mostly appear at the edges or corners of the image. Therefore, the collaborative downscaled images are able to provide more information for those high-frequency regions, which are often difficult to reconstruct during the upscaling process.

Figure I. Visualization of the generated collaborative LR examples and the corresponding perturbations. These visualization results indicate that the generated collaborative examples are able to provide more information for those high-frequency regions.

B. Visualization of Reconstructed Images

Recently, many efforts have been made to improve the visual quality of the images [5, 2, 1, 6]. As shown in Figures II and III, we provide visual comparisons for our HCD based on the image rescaling methods IRN [5] and HCFlow [2], and the original method Bicubic [4]. Our method can eliminate the noise brought by the original model, making the lines smoother and the details more realistic, while other baselines may give more distorted ones. Especially, in the first row of Figure II, our method can alleviate the color bias brought by the HCFlow.

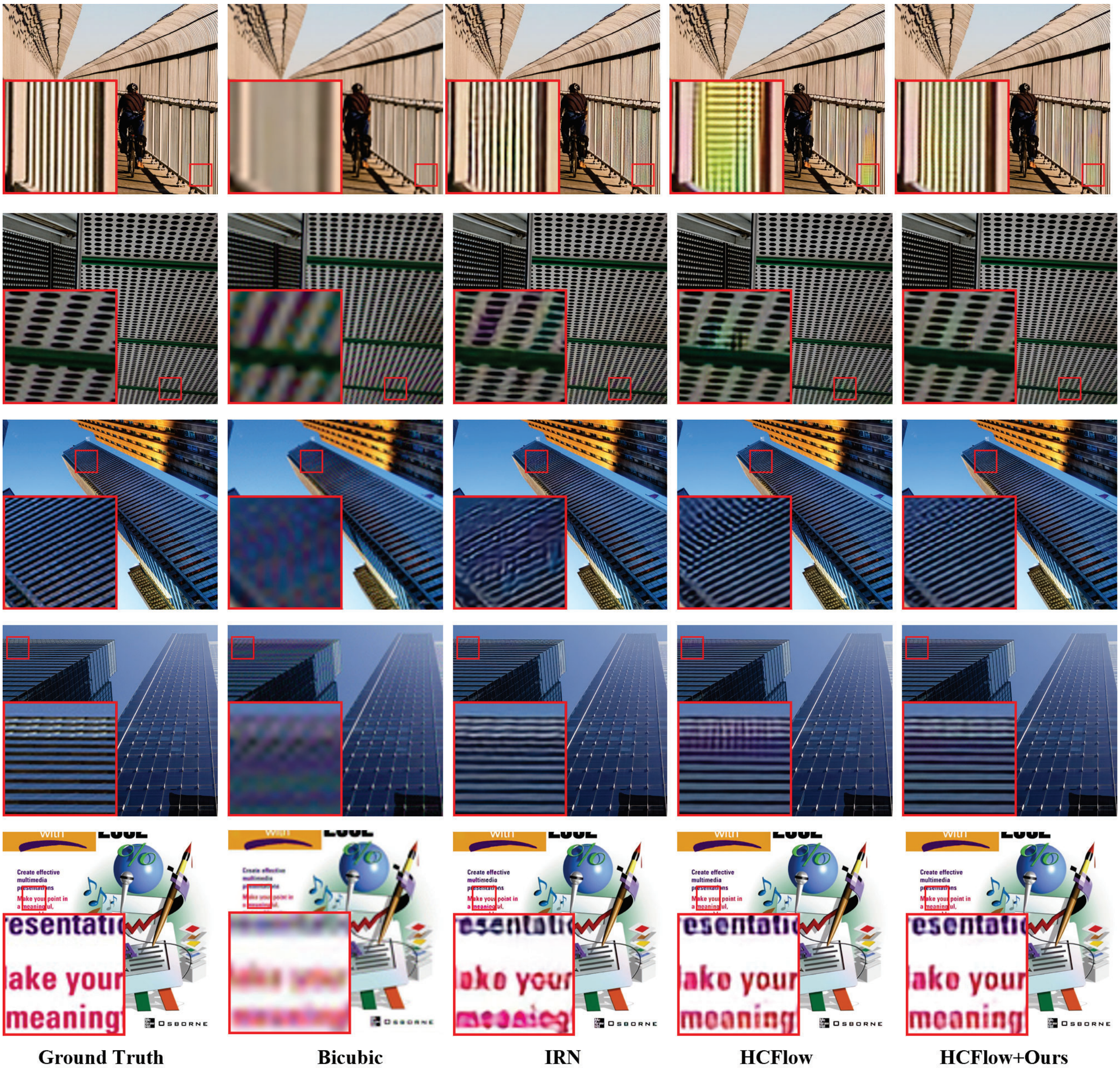

Figure II. Qualitative results of upscaling the $4\times$ downscaled images. Our HCD with HCFlow is able to produce images with sharper edges and more realistic details than baseline methods. In addition, we can also eliminate the wrong lines generated by the original model.

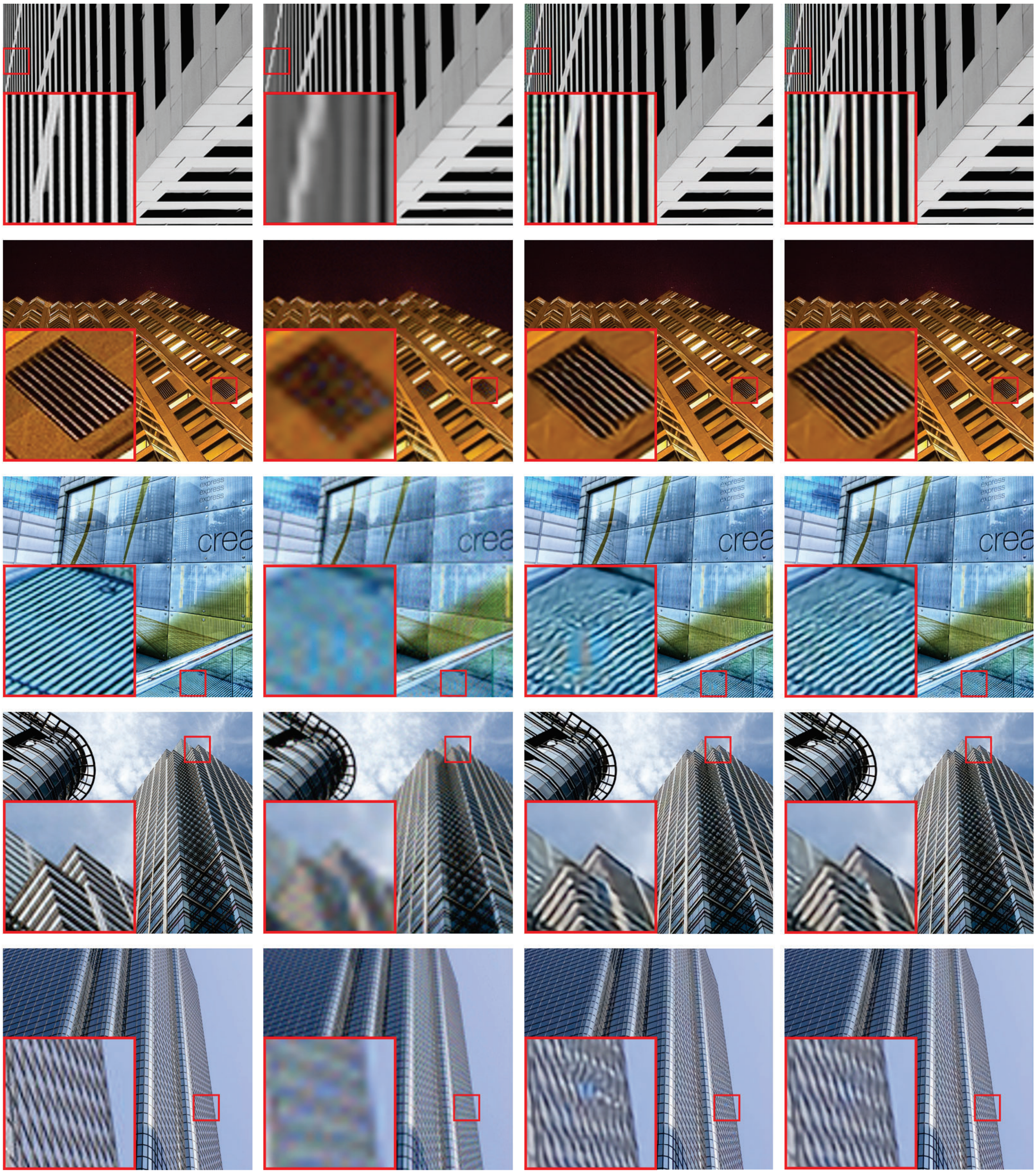

Figure III. Qualitative results of upscaling the 4× downscaled images. Our HCD with IRN can better restore continuous edges and produce sharper HR images, which results in more realistic visual quality.

C. Visualization of Downscaled Images

As shown in Figures IV and V, images downscaled by HCD-optimized IRN and HCFLow have similar visual perceptions to images downscaled by bicubic. The visualization results show that our method not only improves the reconstruction performance of upscaled models but also guarantees the visual perception of the downscaled images and performs as well as bicubic. Therefore, the obtained LR images can also be applied to low-resolution scenes.

Figure IV. Visualization of the downscaled images. Top row: Images downscaled by bicubic. Bottom row: Images downscaled by HCD based on IRN. They share a similar visual perception.

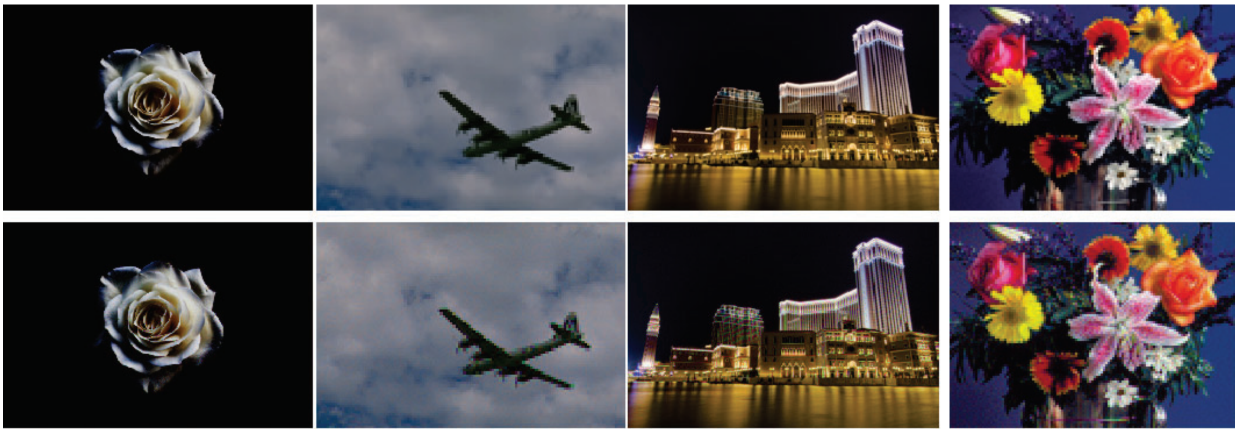

Figure V. Visualization of the downscaled images. Top row: Images downscaled by bicubic. Bottom row: Images downscaled by HCD based on HCFlow. They share a similar visual perception.

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