Structure-Preserving Super Resolution with Gradient Guidance Supplementary Material

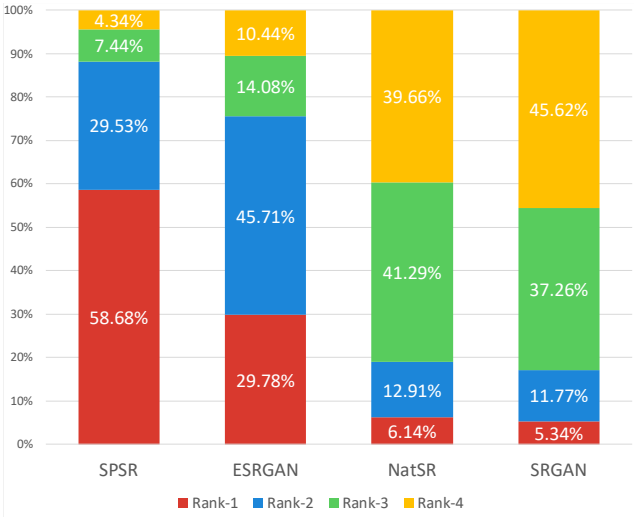


Figure 1. User study results of different GAN-based SR methods. Our SPSR method outperforms state-of-the-art SR methods in generating high-quality images.

1. User Study

We conduct a user study as a subjective assessment to evaluate the visual performance of different SR methods on benchmark datasets. HR images are displayed as references while SR results of our SPSR method, ESRGAN [5], NatSR [3] and SRGAN [1] are presented in a randomized sequence. Human raters are asked to rank the four SR versions according to the perceptual quality. Finally, we collect 1290 votes from 43 human raters. The summarized results are presented in Figure 1. As shown, our SPSR method gets much more votes of rank-1 than ESRGAN, NatSR and SRGAN. Meanwhile, most SR results of ESRGAN are voted the second best among the four methods since there are more structural distortions in the recovered images of ESRGAN than ours. NatSR and SRGAN fail to obtain satisfactory results. We think the reason is that they sometimes generate relatively blurry textures and undesirable artifacts. The comparison with the state-of-the-art GAN-based SR methods verifies the superiority of our proposed method in generating high-fidelity SR results.

2. More Qualitative Results

2.1. SR Comparison

We display more SR performance comparison with state-of-the-art SR methods including EnhanceNet [2], SFT-GAN [4], SRGAN [1], ESRGAN [5] and NatSR [3], as shown in Figure 2, Figure 3, Figure 4, Figure 5 and Figure 6. The results show the proposed SPSR method performs better than other SR methods in recovering structural-pleasant and photo-realistic images.

2.2. Visualization of Gradient Maps

We visualize the outputs of the gradient branch, as shown in Figure 7. We can see the gradient branch succeeds in converting LR gradient maps to the HR ones.

References

[1] Christian Ledig, Lucas Theis, Ferenc Huszár, Jose Caballero, Andrew Cunningham, Alejandro Acosta, Andrew Aitken, Alykhan Tejani, Johannes Totz, Zehan Wang, et al. Photo-realistic single image super-resolution using a generative adversarial network. In *CVPR*, pages 4681–4690, 2017. 1

[2] Mehdi SM Sajjadi, Bernhard Scholkopf, and Michael Hirsch. Enhancenet: Single image super-resolution through automated texture synthesis. In *ICCV*, pages 4491–4500, 2017. 1

[3] Jae Woong Soh, Gu Yong Park, Junho Jo, and Nam Ik Cho. Natural and realistic single image super-resolution with explicit natural manifold discrimination. In *CVPR*, pages 8122–8131, 2019. 1

[4] Xintao Wang, Ke Yu, Chao Dong, and Chen Change Loy. Recovering realistic texture in image super-resolution by deep spatial feature transform. In *CVPR*, pages 606–615, 2018. 1

[5] Xintao Wang, Ke Yu, Shixiang Wu, Jinjin Gu, Yihao Liu, Chao Dong, Yu Qiao, and Chen Change Loy. Esrgan: Enhanced super-resolution generative adversarial networks. In *ECCV*, pages 63–79. Springer, 2018. 1

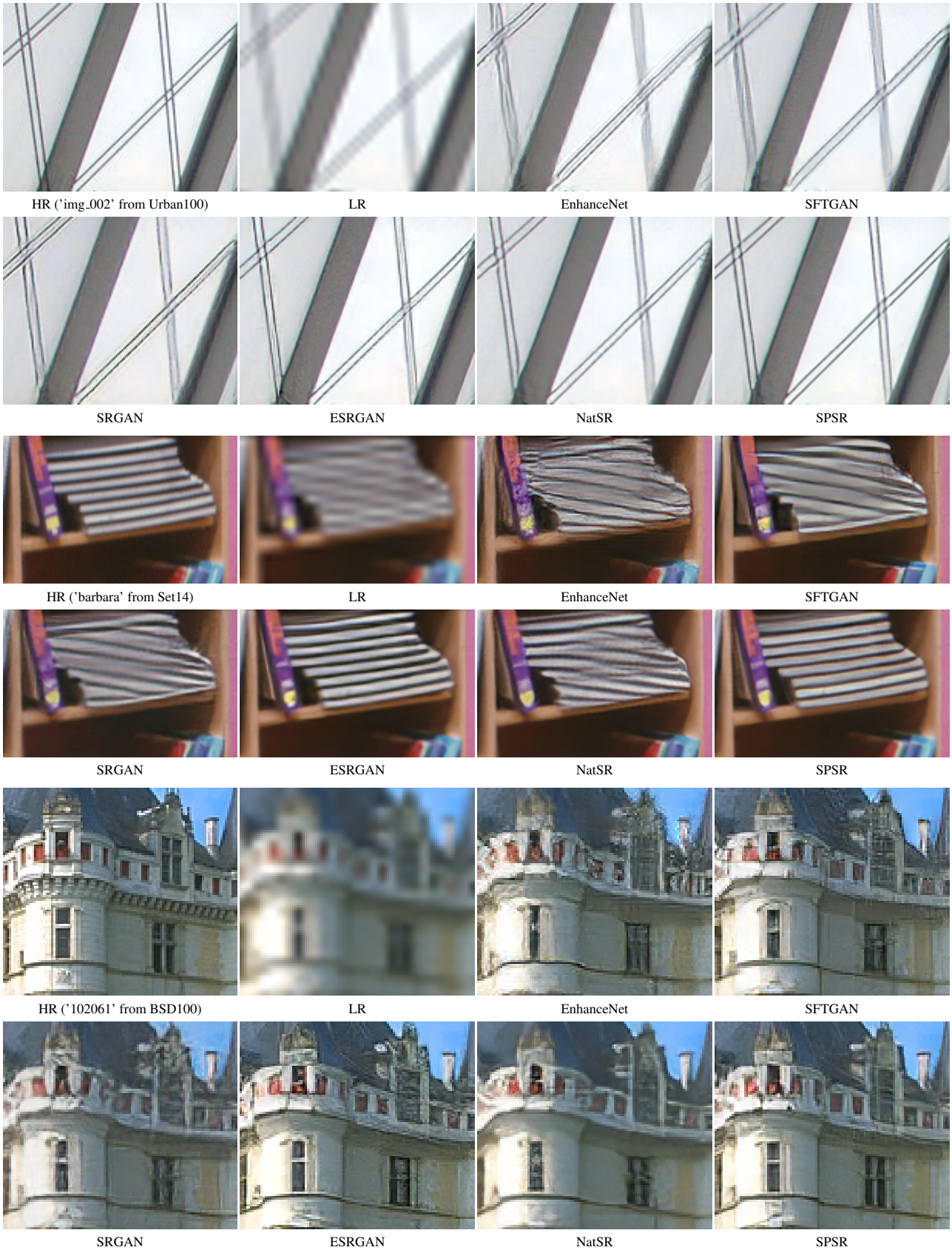


Figure 2. Visual comparison of SR performance with state-of-the-art SR methods.

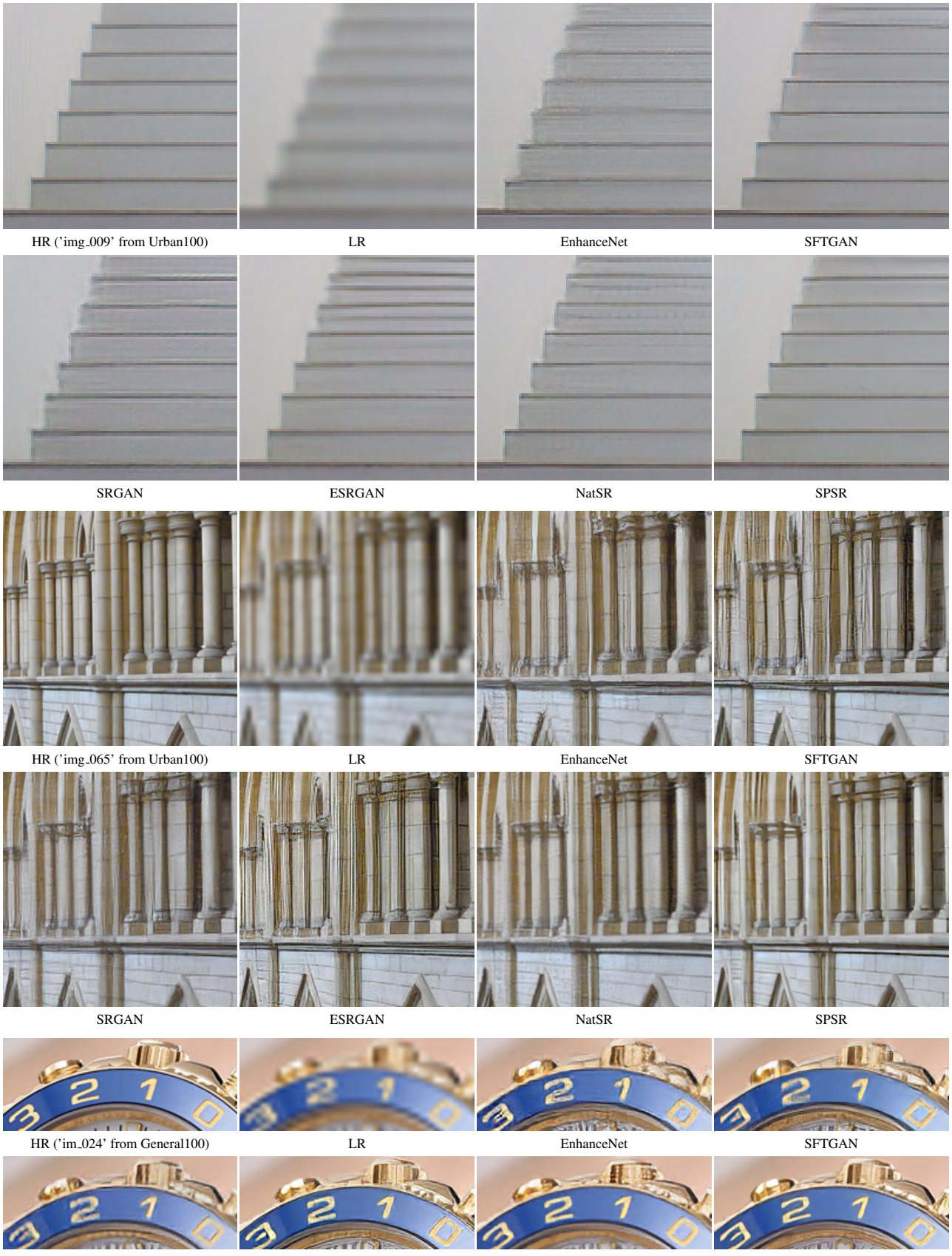


Figure 3. Visual comparison of SR performance with state-of-the-art SR methods.

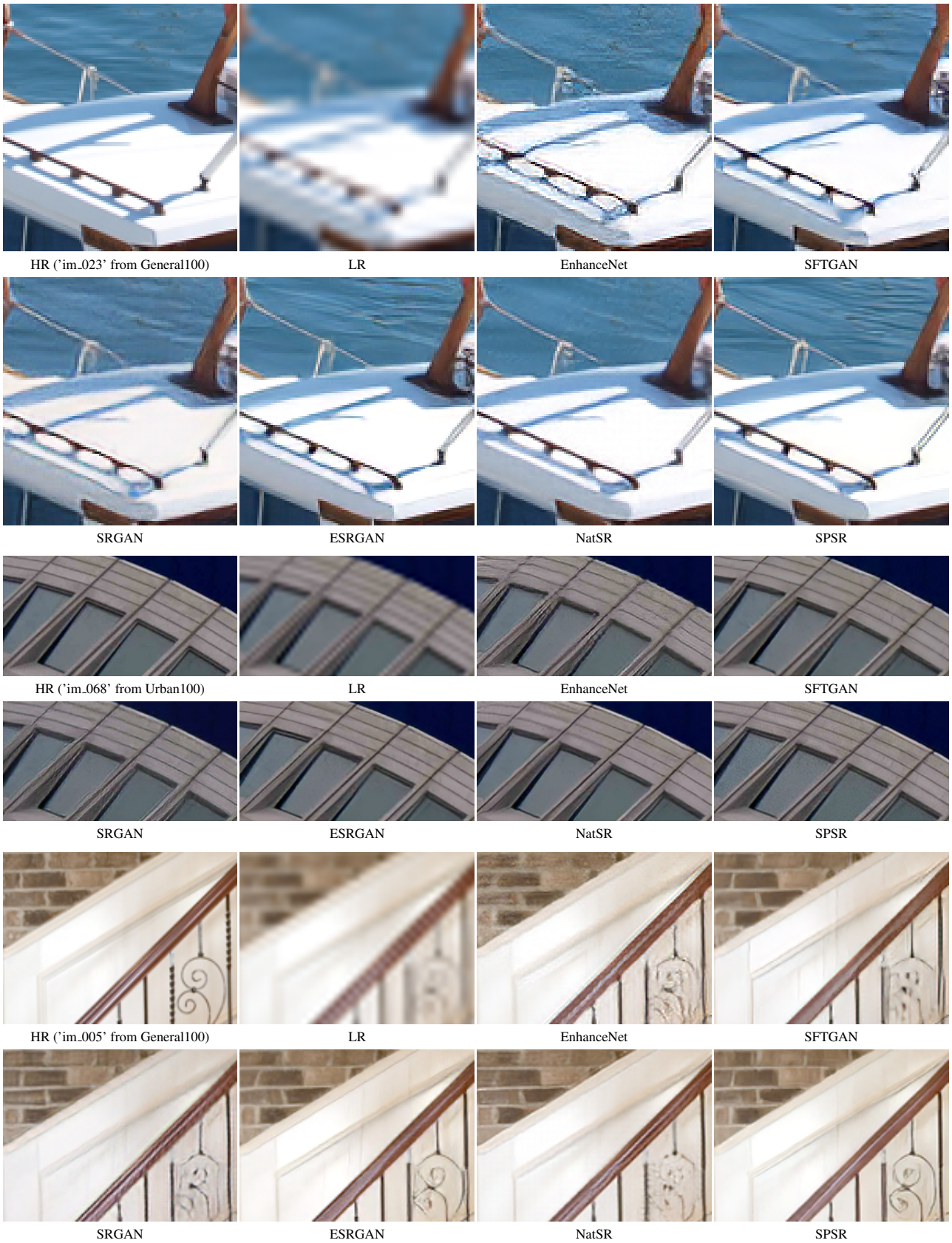


Figure 4. Visual comparison of SR performance with state-of-the-art SR methods.

HR ('img_077' from Urban100) LR EnhanceNet SFTGAN

SRGAN ESRGAN NatSR SPSR

HR ('im_008' from General100) LR EnhanceNet SFTGAN

SRGAN ESRGAN NatSR SPSR

Figure 5. Visual comparison of SR performance with state-of-the-art SR methods.

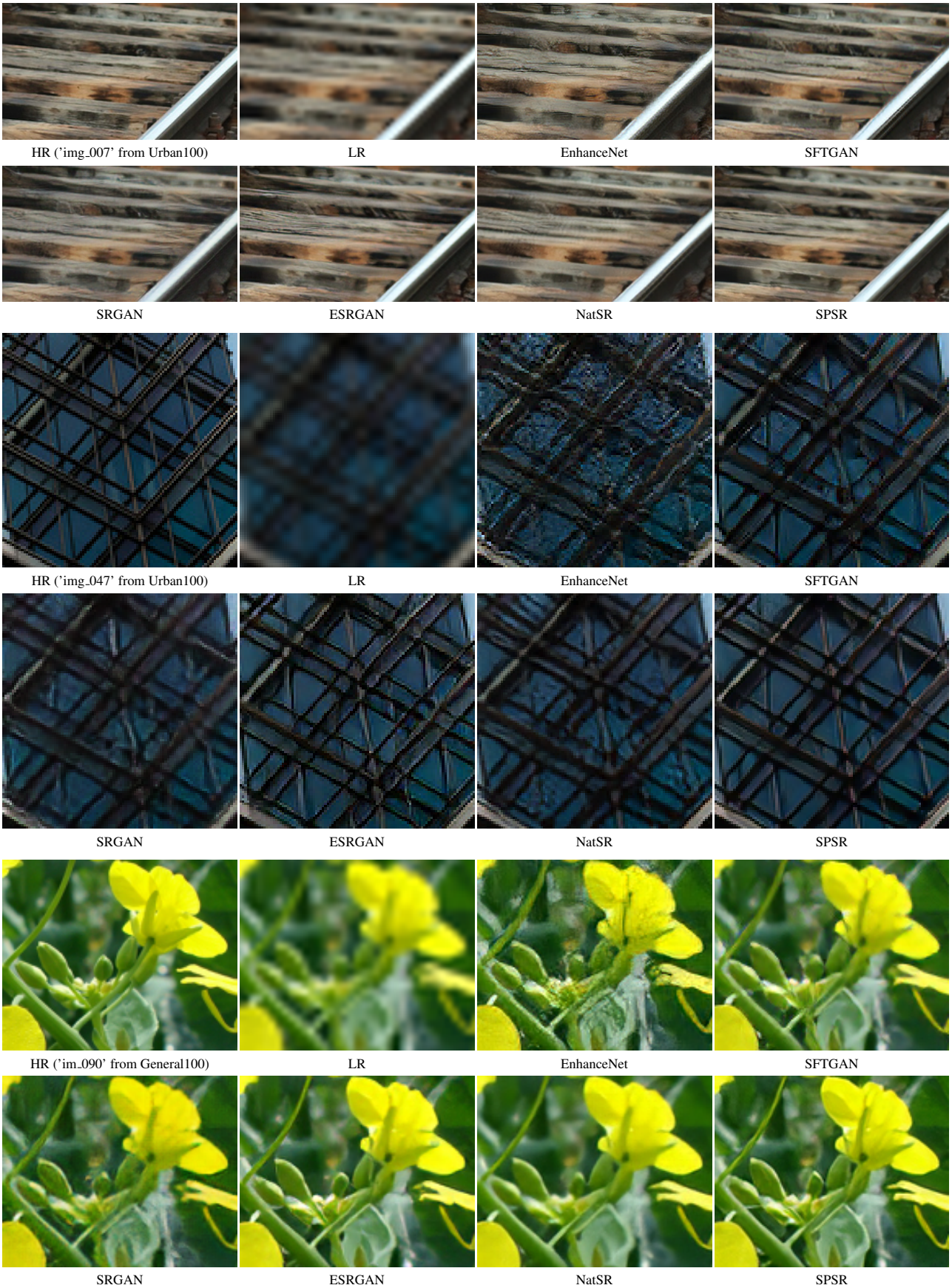
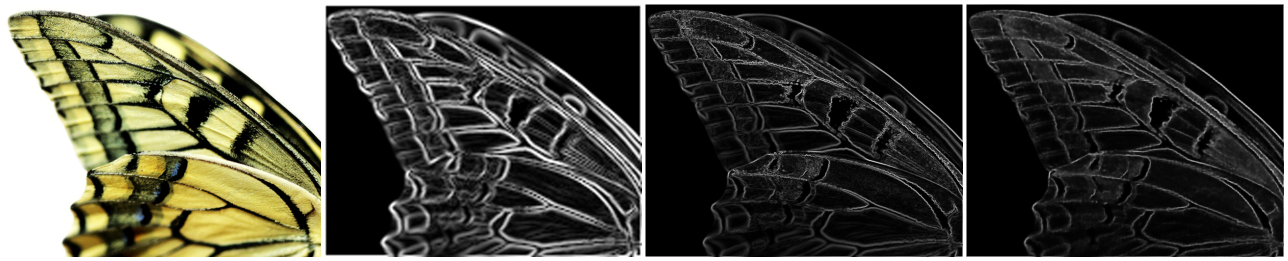
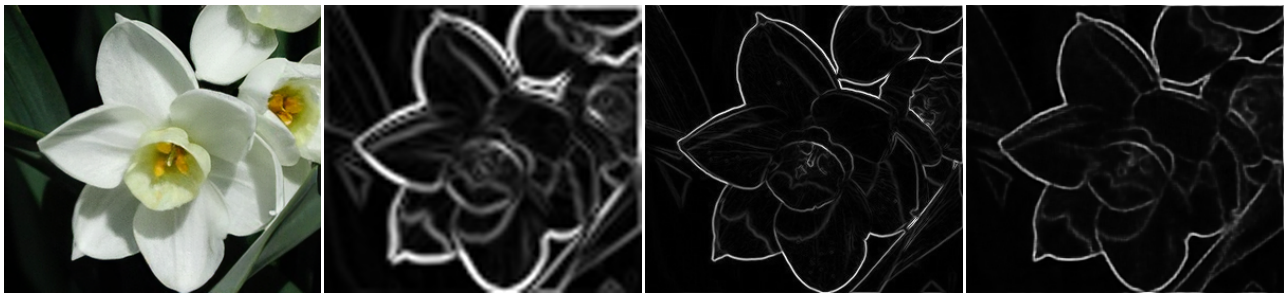


Figure 6. Visual comparison of SR performance with state-of-the-art SR methods.



HR ('im_014' from General100) LR gradient (Bicubic) HR gradient Output of the gradient branch

HR ('im_026' from General100) LR gradient (Bicubic) HR gradient Output of the gradient branch



HR ('im_055' from General100) LR gradient (Bicubic) HR gradient Output of the gradient branch

HR ('img_025' from Urban100) LR gradient (Bicubic) HR gradient Output of the gradient branch

Figure 7. Visualization of gradient maps.