

# Supplementary File of SIR-SRGAN: Super-Resolution Generative Adversarial Network with Self-Interpolation Ranker

Jun-Hong Huang<sup>1</sup>  
[xx1217522411@outlook.com](mailto:xx1217522411@outlook.com)  
 Hai-Kun Wang<sup>1</sup>  
[wanghaikun@gmail.com](mailto:wanghaikun@gmail.com)  
 Yong Yu<sup>2</sup>  
[pzhyuyong@126.com](mailto:pzhyuyong@126.com)  
 Zhi-Wu Liao<sup>1</sup>  
[liaozihiwu@163.com](mailto:liaozihiwu@163.com)

<sup>1</sup>The college of computer science  
 Sichuan Normal University  
 Chengdu, China  
<sup>2</sup>The college of mathematics and  
 computers  
 Panzhihua University  
 Panzhihua, China

## Abstract

This supplementary document will introduce Ranker's design and provide more visual quality comparisons of images.

## 1. Detail of Ranker

### 1.1 Network Architecture

Considering that the overall architecture of the pixel domain Ranker's functionality is essentially the same as that used by the same, the overall architecture is essentially the same showing in Figure 1.

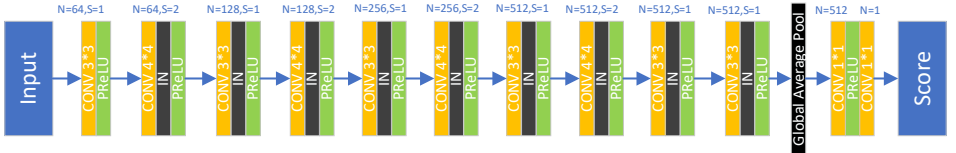


Figure 1. The architecture of Pixel Ranker. N is the number of convolution kern; S is the stride of convolution.

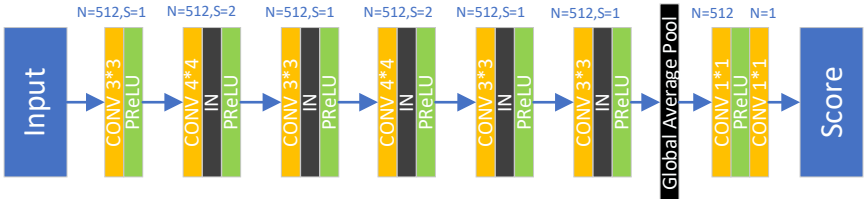


Figure 2. The architecture of Feature Ranker. N is the number of convolution kern; S is the stride of convolution.

Feature Ranker is essentially the same structure as Pixel Ranker and has fewer layers due to input size limitations. Its structure is showing in Figure 2.

Similarly, we used SCROCC[1] to analyze Ranker's performance; a higher value means better performance. We use the BSD100 as a test set for Ranker performance testing. The interpolation factors for the interpolated images participating in the sort are [0, 0.25, 0.5, 0.75]. The results and ablation experiments are showing in Table 1.

	Pixel Ranker		Feature Ranker	
Model	VGG16[2]	Ours	Ours	VGG16
SROCC	0.9652	0.9648	0.8420	0.8424

Table 1. The performance of Ranker on different models in sorting.

Although using the VGG16 model can get better performance, we chose a smaller Ranker model, considering that the difference was not significant and that the training time would multiply.

## 1.2 The choice of interpolation factor

There are many kinds of interpolation factors, and we mainly experimented with 4 kinds of value-taking methods. The results are showing in Table 2.

	Pixel Ranker				Feature Ranker			
Factor	A	B	C	D	A	B	C	D
SROCC	0.8962	0.9542	0.9590	0.9648	0.7856	0.8334	0.8388	0.8424

Table 2. Comparison of the performance effects of different interpolation shadows on Ranker.

A's interpolation factor are [0,0.2,0.4,0.6,0.8,1], B's factor are [0,0.2,0.4,0.6,0.8], C's interpolation factor are [0,0.1,0.3,0.5,0.7,0.9] and the interpolation factor of D is used by us in the article.

## 2. More Qualitative Compare

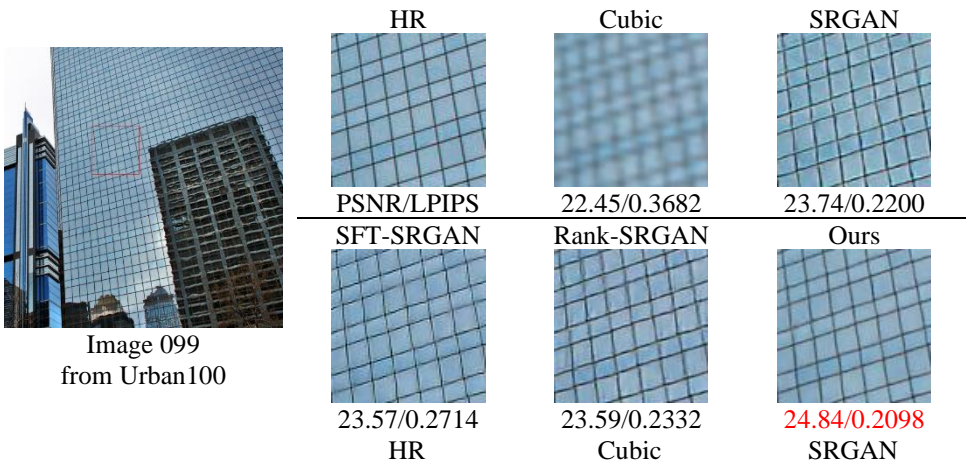
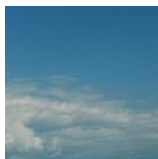
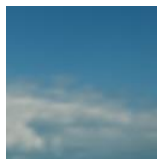




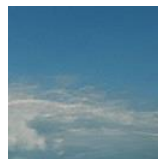
Image 14037  
from BSD100



PSNR/LPIPS



SFT-SRGAN

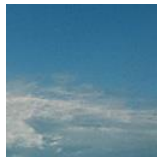


Rank-SRGAN

Ours



32.66/0.1812



32.25/0.2107



33.16/0.1777

HR

Cubic

SRGAN

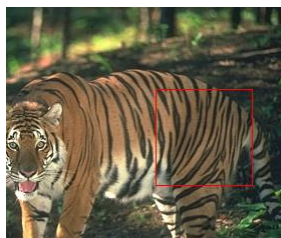
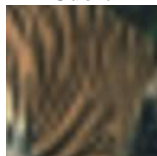


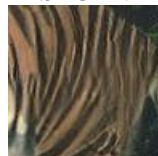
Image 108005  
from BSD100



PSNR/LPIPS



SFT-SRGAN



Rank-SRGAN

Ours



24.72/0.2717



24.29/0.2982



25.14/0.2717

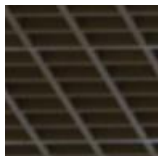
HR

Cubic

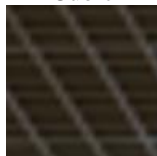
SRGAN



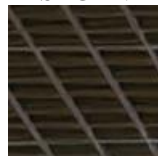
Image 044 from U100



PSNR/LPIPS

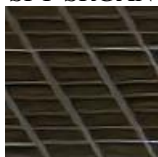


SFT-SRGAN

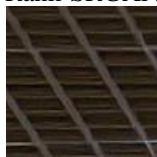


Rank-SRGAN

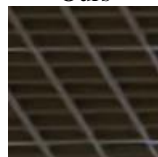
Ours



26.98/0.2315



29.06/0.2150



31.34/1.783



Image 032  
from Urban100

HR	Cubic	SRGAN
PSNR/LPIPS	26.01/0.3560	27.27/0.2166
SFT-SRGAN	Rank-SRGAN	Ours
26.60/0.2298	27.20/0.2555	27.97/0.2130



Image 029  
from PIRM-Test

HR	Cubic	SRGAN
PSNR/LPIPS	30.16/0.2984	31.10/0.1573
SFT-SRGAN	Rank-SRGAN	Ours
30.21/0.1966	30.91/0.1662	31.93/0.1498



Image 022  
from PIRM-Test

HR	Cubic	SRGAN
PSNR/LPIPS	27.39/0.2990	27.27/0.1918
SFT-SRGAN	Rank-SRGAN	Ours
26.38/0.2157	26.75/0.1860	27.94/0.1779

## References

- [1] Xialei Liu, Joost van de Weijer, and Andrew D Bagdanov. Rankiqqa: Learning from rankings for no-reference image quality assessment. Computer Vision and Pattern Recognition, <https://arxiv.org/abs/1707.08347> v1, 2017
- [2] Simonyan K, Zisserman A. Very Deep Convolutional Networks for Large-Scale Image Reco

- gnition[J]. Computer Science, 2014.
- [3] Marco Bevilacqua, Aline Roumy, Christine Guillemot, and Marie-Line Alberi-Morel. Low-complexity single-image super-resolution based on nonnegative neighbor embedding. In BMVC, 2012.
  - [4] Roman Zeyde, Michael Elad, and Matan Protter. On single image scale-up using sparse-representations. In ICCS, pages 711–730. Springer, 2010.
  - [5] Sridhar S. Mallick. A database of human segmented natural images and its application to evaluating segmentation algorithms and measuring ecological statistics. In ICCV, pages 416–425, 2001.
  - [6] Jia-Bin Huang, Abhishek Singh, and Narendra Ahuja. Single image super-resolution from transformed self-exemplars. In CVPR, pages 5197–5206, 2015.
  - [7] Chao D, Chen C L, Tang X. Accelerating the Super-Resolution Convolutional Neural Network[C]// European Conference on Computer Vision. Springer, Cham, 2016.
  - [8] Zhang R, Isola P, Efros A A, et al. The Unreasonable Effectiveness of Deep Features as a Perceptual Metric[C]// IEEE/CVF Conference on Computer Vision & Pattern Recognition. IEEE, 2018.