Image Super-Resolution Optimization Based on Mosaic and GAN

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Introduction

Like many such inverse problems, image super resolution is challenging because multiple output images may be consistent with a single input image, and the conditional distribution of output images given the input typically does not conform well to simple parametric distributions

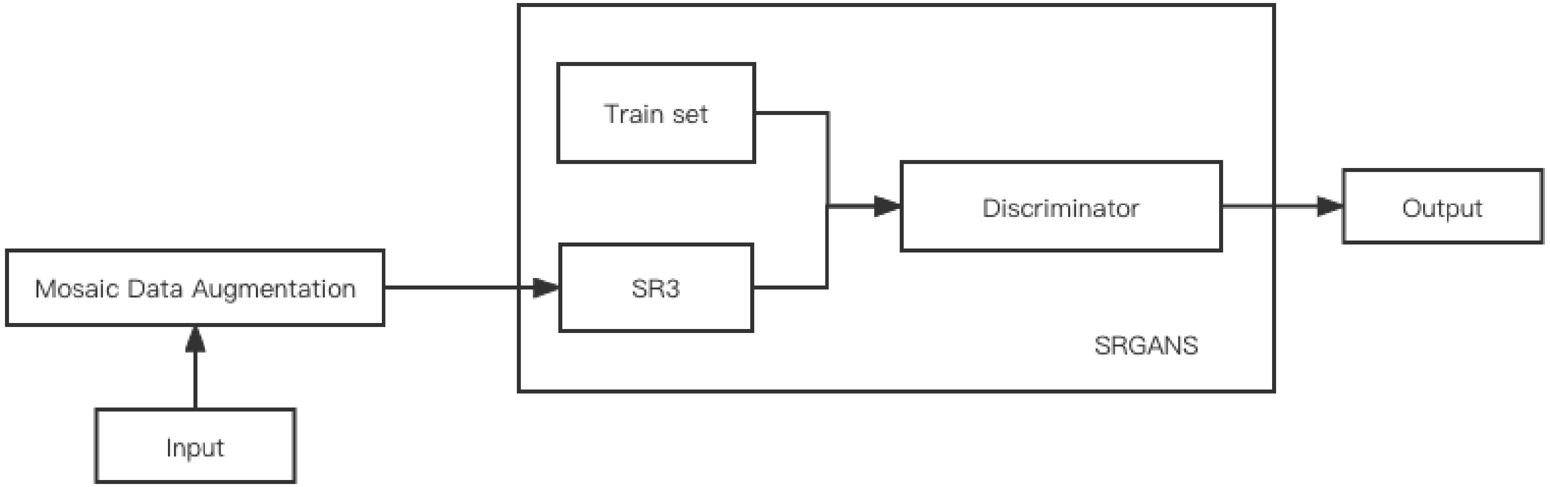
The ill-conditioned nature of the underdetermined SR problem is especially pronounced for high magnification factors, since texture details are usually absent in the reconstructed SR image.

In some projects the dataset may not be sufficient.

①Solve the problem of insufficient own dataset data.

②Try to improve fidelity with GAN. According to the Brock et al.(2018),GAN it may be helpful for improving the fidelity details .

Method

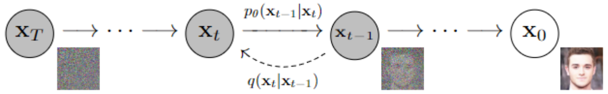


① Adding Mosaic Data Augmentation makes the data set more abundant.

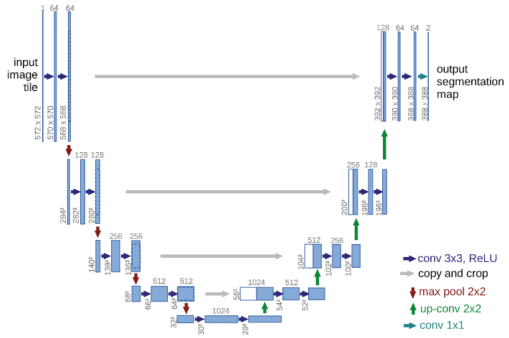
② Add SRGANS to the existing ISR(SR3) to try to improve the fidelity.

Method-SR

Denoising Diffusion Probabilistic Models(J Ho et al,2020):
Each timestep t corresponds to a certain noise level and x_t can be thought of as a mixture of a signal x_0 and some noise ε. Therefore, a diffusion model is essentially a Markov chain model trained to produce samples matching the original data after finite time.



Our SR adapts DDPM to conditional image generation by proposing a simple and effective modification to the U-Net architecture(Ronneberger O et al,2015).
The way to achieve ISR is Repeated Re-finement.

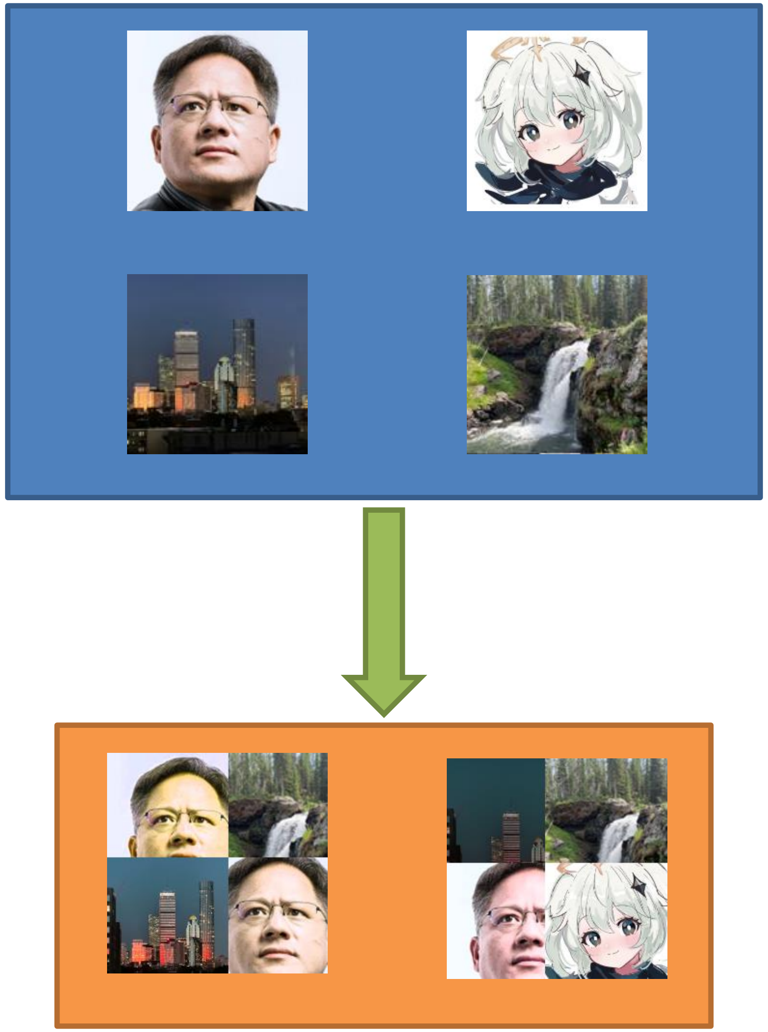


Method-SR

Method -Mosaic

1； Image Processing

1. Read **4 picture** at one time each time
2. Pass the 4 **picture** to function **get_random_data**
3. In the **get_random_data** function, 4pictures will be traversed,flipped, zoomed, and the color gamut ,will be changed to obtain **4 new pictures**.
4. Place the obtained **4 new pictures** in the four corners of the pictures respectively;placed according to place_x and place_y in **get_random_data**



2; Stitching of pictures

5. First look for the dividing line. There are obvious edges when splicing. The horizontal and vertical lines are the dividing lines. The dividing line is determined by the min_offset_x and min_ffset_y we defined in the get_random_data function
6. When we finally divide the picture and put it together, we will use min_offset_x and min_offset_y to select the dividing line
8. After completing the selected dividing line, use cutx and cuty in the get_random_data function to copy the adjusted four pictures to the new picture.

Dataset -Mosaic

Dataset 1:Face Photo*3000 + Landscape Photo*800;
Total 3800
(Non-Mosaic)

Dataset 2: Mosaic Face Photo*1500 + Mosaic Landscape Photo*400;
Total 1900
(Mosaic ; generated from Dataset1)

Dataset 3:Face Photo*3000 + Landscape Photo*800+ Mosaic Face Photo*1500 + Mosaic Landscape Photo*400;
Total 5700
(Non-Mosaic+ Mosaic)

Face Photo from CelebAMask-HQ
Landscape Photo from DIV-2K

Result -Mosaic

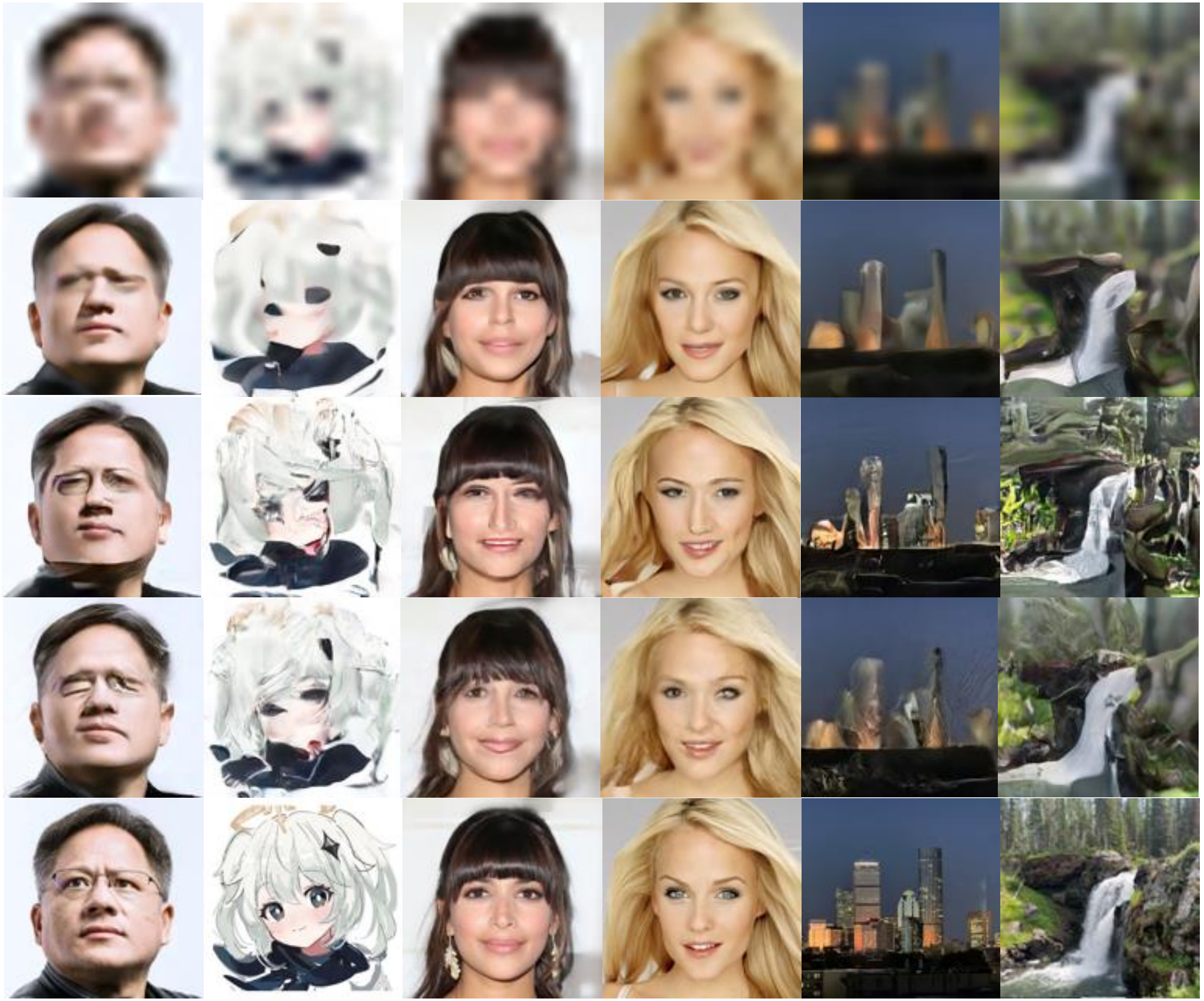
Input

(Non-Mosaic)

(Mosaic)

(Non-Mosaic+ Mosaic)

Original



Result -Mosaic

The results generated using only mosaic data have a very obvious sense of segmentation.

Dataset Total 3800
(Non-Mosaic)

Dataset Total 5700
(Non-Mosaic+ Mosaic)

The mosaic technology is used to expand the data set, and the resolution of the graphics can be improved to obtain better fidelity and details.

Result -Mosaic

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	Dataset Total 3800 (Non-Mosaic)	Dataset Total 5700 (Non-Mosaic+ Mosaic)
PSNR	1.95	2.29 ↑
SSIM	0.501	0.685 ↑

Method-SRGAN

Discussion & Conclusion

The mosaic technology is used to expand the data set, and the resolution of the graphics can be improved to obtain better fidelity and details.

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