Image Super-Resolution using GAN

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Abstract

Andrian Bulat et.al. has proposed a new technique [1] for image super resolution. He has used a separate GAN for learning noise pattern in realistic low-resolution images. This GAN model is used for generating paired dataset of high-resolution images and their respective low-resolution images. The paired dataset generated is used for training another GAN model which super resolves the low-resolution image to high-resolution.

Author has claimed that this technique outperforms all prior state-of-the-art techniques. Through this project, we are trying to validate the author's claim by re-implementing this proposed technique and test it on other datasets.

Introduction

Project Task:

Increase the resolution and quality of low-resolution image to generate respective high-resolution image. This is referred as Image Super Resolution. It is one of the hot research topic in computer vision field and will be very useful in many applications like as improving quality of surveillance footage, improve image capturing ability of mobile devices without significant change in base hardware, etc.

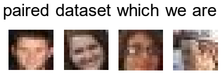
Methods:

Unlike other prior known techniques [5] of image super resolution, author has used two GAN models instead of one. It differs from all other prior works in two points: 1. Method of generating low resolution images and 2. Loss function. Author used first GAN model to learn the common trend in real-world low-resolution image and use it to create paired dataset. Similar to other, author has used second GAN model to super resolve low-resolution image and generate high-resolution image.

Dataset

a. LR Dataset: We are using low resolution images from Widerface [2] dataset to train high-to-low discriminator.

b. HR Dataset: We are using high resolution images from CelebA [3] dataset firstly to train high-to-low generator and then to generate paired dataset which we are using for training low-to-high GAN.



(a) LR Images

(b) HR Images

Model

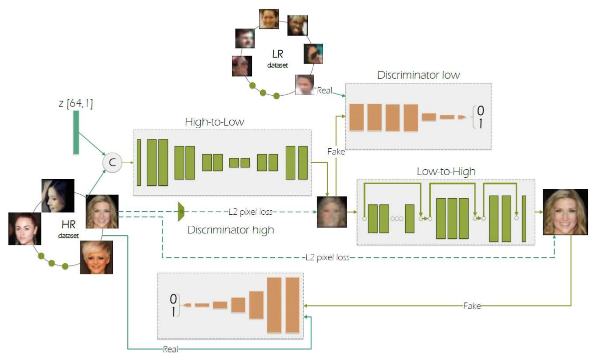


Fig 1. High-to-Low and Low-to-High models

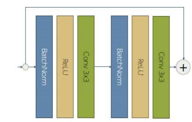


Fig 2. Residual block used for generator

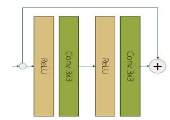


Fig 3. Residual block used for discriminator

*Figure1,2,3: Images are reprinted from [1]

Loss Function

For each network,

$$l = \alpha l_{pixel} + \beta l_{GAN}$$

$$l_{GAN} = \mathop{\mathbb{E}}_{x \sim \mathbb{P}_r}[\min(0, -1 + D(x))] + \mathop{\mathbb{E}}_{\hat{x} \sim \mathbb{P}_g}[\min(0, -1 - D(\hat{x}))]$$

$$l_{pixel} = \frac{1}{WH} \sum_{i=1}^{W} \sum_{j=1}^{H} (F(I^{hr})_{i,j} - G_{\theta_G}(I^d)_{i,j})^2$$

where,

$D(x)$: discriminator output for real images
$D(\hat{x})$: discriminator output for fake images
W : width of generated image
H : height of generated image
F : function which maps resolution of real image and generated image

- l_{GAN} is the adversarial loss of the GAN model (discriminator loss),
- l_{pixel} is pixel loss (L2 distance between original input image to generator and generated image),
- l is loss of the model which is weighted sum of adversarial loss and pixel loss.

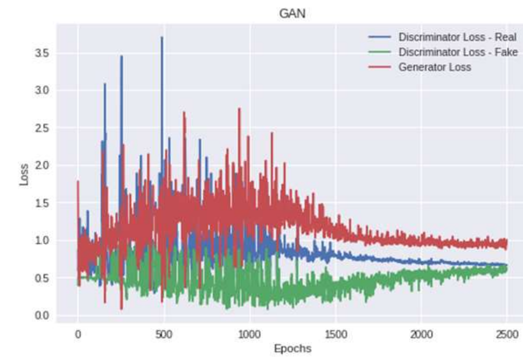
Our Contribution

- We reimplemented the proposed technique to validate the claim made by author that this technique outperforms all state-of-the-art image super resolution methods.
- We are testing the model with other dataset.
- We tried to use only low-to-high GAN model with author's loss function on artificially generated paired dataset by bilinear down-sampling.

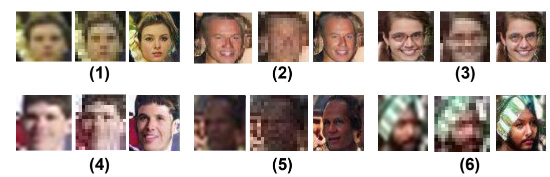
Model evaluation

- Model has two GAN models. High-to-Low GAN to generate paired dataset and Low-to-High GAN to super resolve the image. For testing purpose only generator of Low-to-High GAN is used.
- Proposed technique uses both pixel loss and GAN loss to train the model as pixel loss alone is not able to denoise the input and produce good results.
- FID [4] is used as metric for evaluation of image quality. We have achieved **94.83** FID value for generated high-resolution image..

Variation of loss during model training:

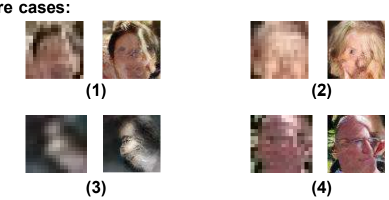


Results



For given all 6 examples, 1st is original image, 2nd is generated low-resolution image and last is generated high-resolution image.

Failure cases:



For given all 4 examples, 1st is original image, 2nd is generated high-resolution image.

REFERENCES

[1] Yang J. Bulat A. and Tzimiropoulos G. "To learn image super-resolution, use a GAN to learn how to do image degradation first". In:"ECCV"("2018").URL http: //arxiv.org/abs/1807.11458
[2] Yang, S., Luo, P., Loy, C.C., Tang, X.: Wider face: A face detection benchmark. In: CVPR. (2016)
[3] Liu, Z., Luo, P., Wang, X., Tang, X.: Deep learning face attributes in the wild. In: ICCV. (2015)
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