

Super-Resolution with GANs

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1. Introduction

We call super-resolution (SR) the task of estimating a high-resolution (HR) image from its low-resolution (LR) counterpart. Recent work with optimization-based methods largely focuses on minimizing the mean squared reconstruction error. This results in high peak signal-to-noise ratios, but they often have problems with modelling high-frequency details. The results are often too smooth. In our work we tried to tackle this problem using generative adversarial networks (GANs).

2. GANs

GANs consist of two different networks, a Generator Network and a Discriminator Network. The concept behind this is that the generative network estimates a super-resolved image from its LR version with the goal to become highly similar to real images that the discriminator network fails to distinguish. Network Architektur einfögen

Therefore we optimize the discriminator network D_{Θ_D} in an alternating manner along with the generative network G_{Θ_G} to solve the adversarial min-max problem:

G_{Θ_G} to solve adversarial min-max problem:

$$\min_{\Theta_G} \max_{\Theta_D} \mathbb{E}_{I^{HR} \sim p_{\text{train}}(I^{HR})} [\log D_{\Theta_D}(I^{HR})] \\ + \mathbb{E}_{I^{HR} \sim p_G(I^{LR})} [\log(1 - G_{\Theta_G}(I^{LR}))]$$

The perceptual loss l^{SR} we defined as weighted sum of a content loss and an discriminative loss component:

$$l^{SR} = \alpha l_{MSE}^{SR} + \beta l_{VGG1619/i.j}^{SR} + \gamma l_D^{SR}$$

More precisely, the content loss components are defined

as follows:

$$l_{MSE}^{SR} = \frac{1}{r^2 W H} \sum_{x=1}^{rW} \sum_{y=1}^{rH} (I_{x,y}^{HR} - G_{\theta_G}(I^{LR})_{x,y})^2 \\ l_{VGG1619/i.j}^{SR} = \frac{1}{W_{i,j} H_{i,j}} \sum_{x=1}^{W_{i,j}} \sum_{y=1}^{H_{i,j}} (\Phi_{i,j}(I^{HR})_{x,y} - \Phi_{i,j}(G_{\Theta_G}(I^{LR}))_{x,y})^2$$

the discriminative loss as follows

$$l_D^{SR} = \sum_{n=1}^N -\log D_{\Theta_D}(G_{\Theta_G}(I^{LR}))$$

3. Setup

3.1. Dataset

For training we used the PASCAL VOC Dataset[3] with more than 10,000 images as well as the NITRE Dataset[1] with 800 images.

3.2. Networks

We used pretrained VGG networks in different configurations. The best results were obtained when we used a VGG1619 network. We also considered a VGG 16 network. Although faster at training it did not yield results of equal quality.

4. Results

5. Conclusion

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