Supplementary File: Learning the Non-differentiable Optimization for Blind Super-Resolution

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Abstract

In this supplementary file, we first provide the details of our proposed adaptive modulation generative adversarial network (AMGAN) and then show the training procedure of AMGAN-RL. Finally, we show more visual results.

1. AMGAN

VGG perceptual loss. The VGG perceptual loss $L_{vgg}$ compares the activation maps in the intermediate layers of well-trained VGG19 [5] network, which can be formulated as

$$L_{vgg} = \sum_{l=1}^{5} w_l \left\| \frac{\psi^{l}_{I_{HR}}}{N^{l}_{I_{HR}}} - \frac{\psi^{l}_{I_{SR}}}{N^{l}_{I_{SR}}} \right\|_1,$$

where $\psi_{I_{HR}}^l$ is the activation map of the relu_1 layer given original input $I_{HR}$, $N_{I_{HR}}$ is the number of elements in $\psi_{I_{HR}}^l$. Following [2], we set $w_l = \frac{1}{e^{(C^{l}_{\psi_{I_{HR}}})^2}}$. Here, $C$ is the channel size of feature map $\psi_{I_{HR}}^l$.

Realness adversarial loss. Different from the standard GAN (including relativistic GAN [3]), RealnessGAN [6]'s discriminator outputs a distribution as the measure of realness.

$$L_{realness} = \mathbb{E}_{I_{HR}\sim \mathcal{P}_{I_{HR}}} \left[ D_{KL} \left( A_1 \parallel D \left( G \left( I_{LR} \right) \right) \right) \right] - \mathbb{E}_{I_{LR}\sim \mathcal{P}_{I_{LR}}} \left[ D_{KL} \left( A_0 \parallel D \left( G \left( I_{LR} \right) \right) \right) \right],$$

where $D_{KL} (\cdot | \cdot)$ denotes Kullback-Leibler (KL) divergence. Two virtual ground-truth distributions are required to stand for the realness distributions of real and fake images. We refer to these two distributions as $A_1$ (real) and $A_0$ (fake). Specifically, $A_1$ and $A_0$ are chosen to resemble the shapes of a Gaussian distribution $\mathcal{N}(0,I)$ and a Uniform distribution $\mathcal{U}(0,I)$, respectively. The architecture of our discriminator is illustrated in Figure 1.

![Figure 1. The structure of our discriminator. “s2” denotes the stride os 2.](image)

Total loss. With L1 loss, VGG perceptual loss, realness adversarial loss, and DIST loss [1], our final loss function is defined as

$$L_{total} = L_1 + 15L_{vgg} + 0.01L_{realness} + 10L_{DISTs}.$$

To validate the effectiveness of the introduced Realness GAN, we conduct the same model trained with Relativistic GAN, denoted by AMGAN*. As shown in Table 1, AMGAN perform superior performance (PSNR & SSIM) than AMGAN*.

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<th>Dataset</th>
<th>Scores</th>
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*Corresponding author
2. The training procedure of AMGAN-RL

The algorithm of the detailed training process is summarized in Algorithm 1.

**Algorithm 1 Training AMGAN-RL**

**Require:** Critic network $Q(s, a | \theta^Q)$ (random initialization); Pretrained actor $\mu(s | \theta^\mu)$; Initialize replay buffer $R$; Initialize Environment with pre-trained renderer AMGAN.

1: for $t_{steps} < maxsteps$ do
2:   Receive initial observation state $s_t$
3:   Select action $a_t = \mu(s_t | \theta^\mu)$ according to the current policy
4:   Execute action $a_t$ and observe reward $r_t$ and observe rendered result $s'_t$
5:   Store transition $(s_t, a_t, r_t, s'_t)$ in $R$
6:   Sample a random minibatch of $N$ transitions $(s_t, a_t, r_t, s'_t)$ from $R$
7:   Update critic by minimizing the loss: $L(\theta^Q) = \frac{1}{N} \sum_i \max (0, -\gamma \cdot Q(s_i, a_i | \theta^Q) + (r_i - Q(s_i, a_i | \theta^Q))$
8:   Update the actor policy using the policy gradient: $\nabla_{\theta^\mu} J = \frac{1}{N} \sum_i \nabla_a Q(s, a | \theta^Q) \Big|_{s=s_i, a=\mu(s_i)} \nabla_{\theta^\mu} \mu(s | \theta^\mu) \Big|_{s=s_i}$
9: return $\text{ISR} = \text{AMGAN}(\text{ILR}, \mu(\text{ILR} | \theta^\mu))$ (Output the final SR result)

3. Visual results

We give more comparisons with methods of DAN [4] (blind) and USRGAN [7] (non-blind) on PIRM_Val (Figure 2), BSD100, and Set5 (Figure 3). It can be found that our AMNet-RL and AMNet_L-RL shows a little bit sharper than DAN. AMGAN produces texture naturally images, and AMGAN-RL generates sharper details.
Figure 2. Visual results of various methods at scaling factor of 4. Note that USRGAN [7] adopts direct downsampling instead of bicubic downsampling, which is more simple than DAN [4] and our proposed method.
Figure 3. Visual results of various methods at scaling factor of 4. Note that USRGAN [7] adopts direct downsampling instead of bicubic downsampling, which is more simple than DAN [4] and our proposed method.
References


