Blur, Noise, and Compression Robust Generative Adversarial Networks

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Project page

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① Introduction

Blur, noise, and compression robust image generation

(a) Training images (b) GAN (baseline) (c) BNCR-GAN (proposed)

Limitation of standard GAN (b)

- Recreates training images faithfully despite image degradation by blur, noise, and compression (a).

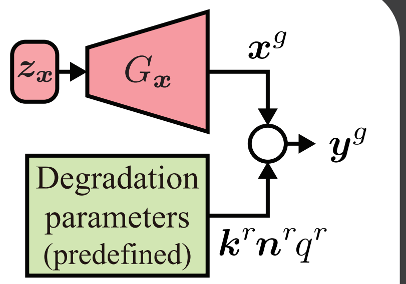
Contribution of BNCR-GAN (c)

- Learns to generate clean images from degraded images (a) without knowledge of degradation parameters (e.g., blur kernel types, noise amounts, or Q factor values).

② Related work

AmbientGAN [Bora+ICLR2018]

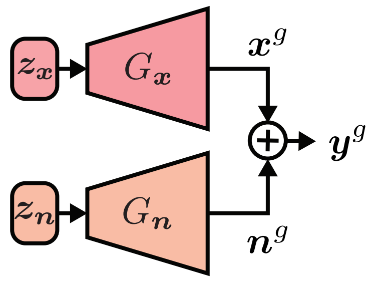
- Learns to generate clean images from degraded images.
- But, requires that degradation parameters are predefined.



AmbientGAN generator

Noise robust GAN: NR-GAN [Kaneko+CVPR2020]

- Eliminates the AmbientGAN requirement by learning a noise generator along with an image generator.
- But, requires that an image and degradation components (i.e., noise) can be decomposed additively.
- -> Challenge to be addressed: Application to irreversible degradation (e.g., blur, compression, and combination of all).



NR-GAN generator

③ Key ideas

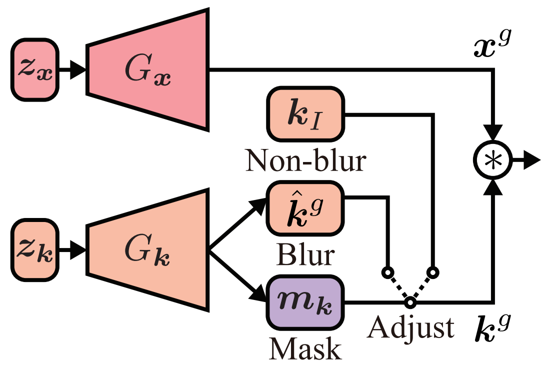
Masking architectures (Mask)

- Adjust degradation strengths in a data-driven manner using bypasses before and after degradation.

Adaptive consistency losses (L_{AC})

- Impose consistency between irreversible degradation processes according to degradation strengths.

④ Blur robust GAN: BR-GAN



BR-GAN generator

BR-GAN Objective

$$\mathcal{L}_{\text{BR-GAN}} = \mathbb{E}_{\boldsymbol{y}^r}[\log D_{\boldsymbol{y}}(\boldsymbol{y}^r)] + \mathbb{E}_{\boldsymbol{z_x},\boldsymbol{z_k}}[\log(1 - D_{\boldsymbol{y}}(G_{\boldsymbol{x}}(\boldsymbol{z_x}) * G_{\boldsymbol{k}}(\boldsymbol{z_k})))]$$

Blurred image; Image; Blur kernel; Convolution

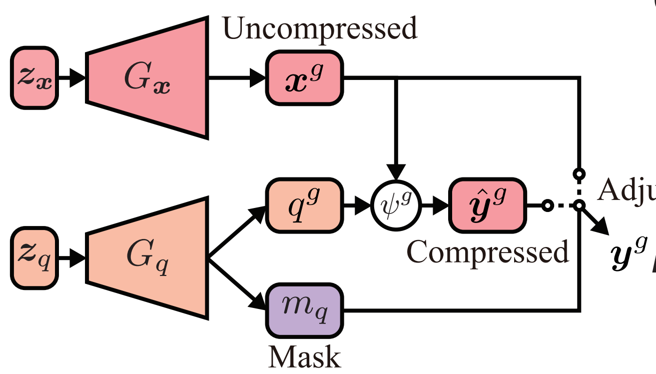
Masking architecture

$$\boldsymbol{k}^g = \boldsymbol{m_k} \cdot \hat{\boldsymbol{k}}^g + (\boldsymbol{1} - \boldsymbol{m_k}) \cdot \boldsymbol{k}_I$$

Mask Blur Non-blur

Blur strength is adjusted by trainable mask.

⑤ Compression robust GAN: CR-GAN



CR-GAN generator

CR-GAN Objective

$$\mathcal{L}_{\text{CR-GAN}} = \mathbb{E}_{\boldsymbol{y}^r}[\log D_{\boldsymbol{y}}(\boldsymbol{y}^r)] + \mathbb{E}_{\boldsymbol{z_x},z_q}[\log(1 - D_{\boldsymbol{y}}(\psi^g(G_{\boldsymbol{x}}(\boldsymbol{z_x}), G_q(z_q))))]$$

Compressed image; Differentiable JPEG; Image; Q factor

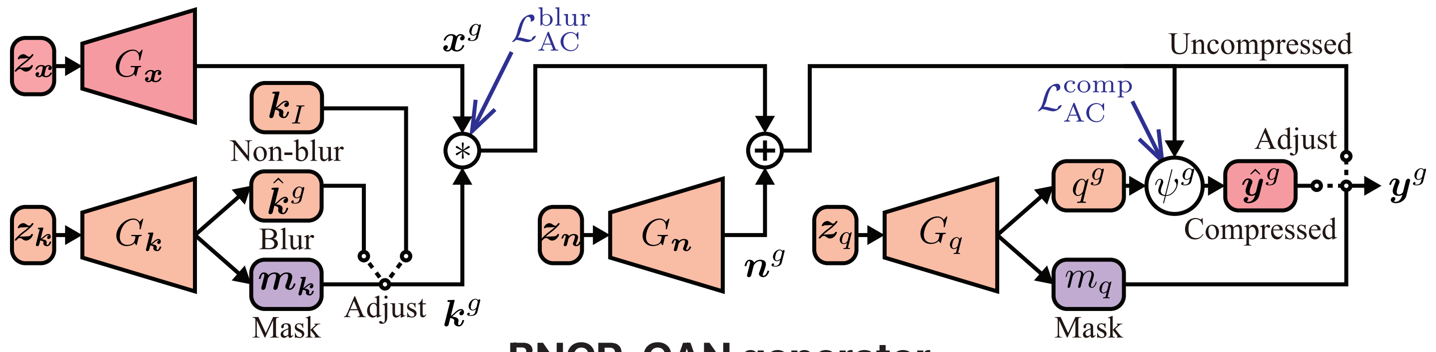
Masking architecture

$$\boldsymbol{y}^g = m_q \hat{\boldsymbol{y}}^g + (1 - m_q)\boldsymbol{x}^g$$

Mask Compressed Uncompressed

Compression strength is adjusted by trainable mask.

⑥ Blur, Noise, and Compression Robust GAN: BNCR-GAN



BNCR-GAN generator

BNCR-GAN Objective

$$\mathcal{L}_{\text{BNCR-GAN}} = \mathbb{E}_{\boldsymbol{y}^r}[\log D_{\boldsymbol{y}}(\boldsymbol{y}^r)] + \mathbb{E}_{\boldsymbol{z_x},\boldsymbol{z_k},\boldsymbol{z_n},z_q}[\log(1 - D_{\boldsymbol{y}}(\psi^g(G_{\boldsymbol{x}}(\boldsymbol{z_x}) * G_{\boldsymbol{k}}(\boldsymbol{z_k}) + G_{\boldsymbol{n}}(\boldsymbol{z_n}), G_q(z_q))))]$$

Blurred, noisy, and compressed image; Image; Blur kernel; Noise; Q factor

Adaptive consistency losses

$$\mathcal{L}_{\text{AC}}^{\text{blur}} = \mathbb{E}_{\boldsymbol{z_x},\boldsymbol{z_k}}[e^{-\mu_k H(G_{\boldsymbol{k}}(\boldsymbol{z_k}))} \|G_{\boldsymbol{x}}(\boldsymbol{z_x}) - G_{\boldsymbol{x}}(\boldsymbol{z_x}) * G_{\boldsymbol{k}}(\boldsymbol{z_k})\|^2]$$

$$\mathcal{L}_{\text{AC}}^{\text{comp}} = \mathbb{E}_{\boldsymbol{z_x},z_q}[e^{-\mu_q \frac{100 - G_q(z_q)}{100}} \|G_{\boldsymbol{x}}(\boldsymbol{z_x}) - \psi^g(G_{\boldsymbol{x}}(\boldsymbol{z_x}), G_q(z_q))\|^2]$$

Adaptive term; Consistency term

Consistency is imposed according to blur/compression strength.

⑦ Comparative and ablation studies on CIFAR-10

Blur robust image generation

FID↓	Blur	½Blur
GAN	43.1	27.4
AmbientGAN	24.2	20.7
BR-GAN	23.4	20.2
BR-GAN w/o mask	26.6	22.9

Compression robust image generation

FID↓	Comp	½Comp
GAN	33.3	24.7
AmbientGAN	40.5	22.8
CR-GAN	26.3	22.7
CR-GAN w/o mask	38.6	31.1

- BR-GAN/CR-GAN outperforms or is comparable to AmbientGAN.
- Mask contributes to improve the performance.

Blur, noise, and compression robust image generation

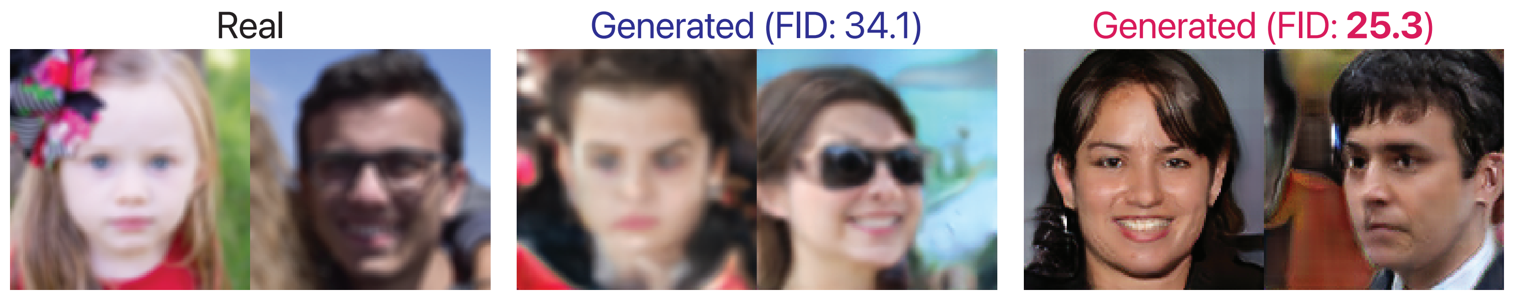
FID↓	B+N+C	½B+N+C
GAN	58.0	34.3
AmbientGAN	46.8	25.6
BR-GAN	52.3	31.6
NR-GAN	58.1	34.6
CR-GAN	51.1	36.8
BNCR-GAN	34.1	25.7
BNCR-GAN w/o $\mathcal{L}_{\text{AC}}$	41.0	28.6

- BNCR-GAN outperforms or is comparable to AmbientGAN.
- L_{AC} contributes to improve the performance.

NOTE: Representative results are selected. See our paper for detailed results.

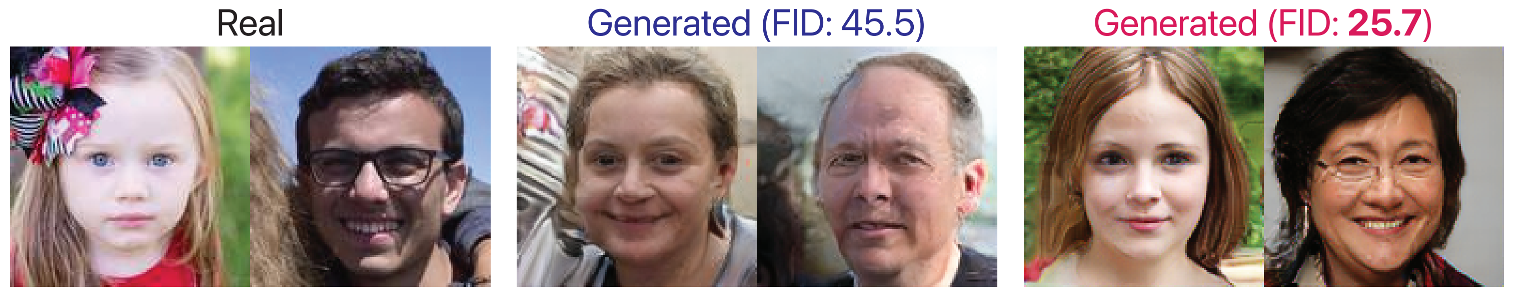
⑧ Examples of generated images on FFHQ

Blur robust image generation



(a) Training images (b) GAN (baseline) (c) BR-GAN (proposed)

Compression robust image generation



(a) Training images (b) GAN (baseline) (c) BR-GAN (proposed)

⑨ Conclusion

- BNCR-GAN can learn to generate clean images from degraded images without knowledge of degradation parameters.
- Mask and L_{AC} are essential components for obtaining this ability.
- Learned degradation models can be used for unsupervised image restoration by incorporating them into UNIR [Pajot+ICLR2019] (see our paper for details).