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Edge Connect: Generative Image Inpainting with Adversarial Edge Learning

Kamyar Nazeri, Eric Ng, Tony Joseph, Faisal Z. Qureshi, Mehran Ebrahimi (2019)

석사과정 3학기 박희성

목차

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목차

1. Edge Connect Introduction

- **Image Inpainting**
  - Image Inpainting, Image Completion은 이미지의 부족한 부분을 채우는 Task

- **Traditional Approaches**
  - Diffusion-based Methods : 주변 pixel value를 missing regions에 propagation 시키는 방식
  - Path-based Methods : 가장 유사한 부분의 path를 missing regions에 붙이는 방식

    > Over-smoothed and/or blurry 문제가 공통적으로 발생함.

(a) Ground Truth (b) Masked Image (c) Yu *et al.* [53] (d) Iizuka *et al.* [22] (e) Ours (f) Ours (Canny)

1. Edge Connect Introduction

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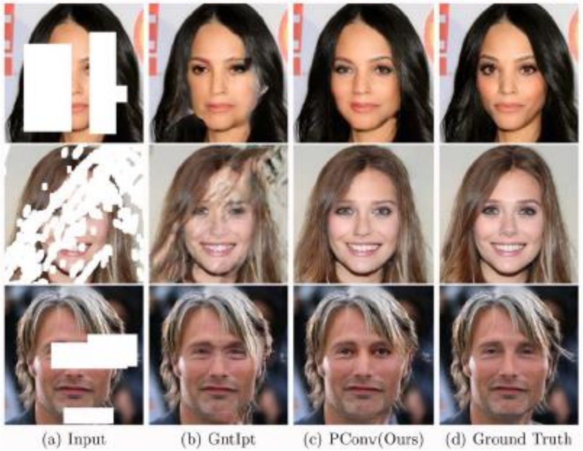
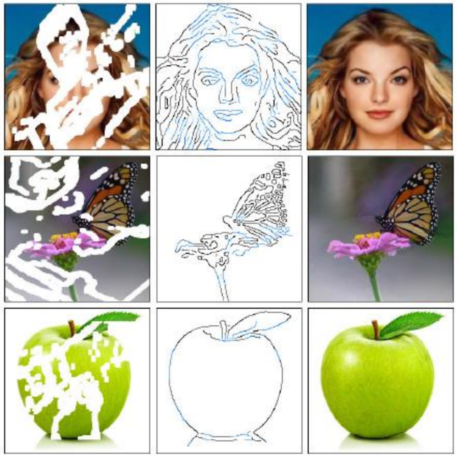
- **Proposing Method**
  - Sketches의 중요성을 강조하며 ‘lines first, color next’ 접근법을 제안
  - ‘**Edge Generator**’ and ‘**Image Completion**’으로 나뉘는 two stage process로 구성되어 있음



<기존 방법론>



<제안 방법론>

1. Edge Connect Introduction

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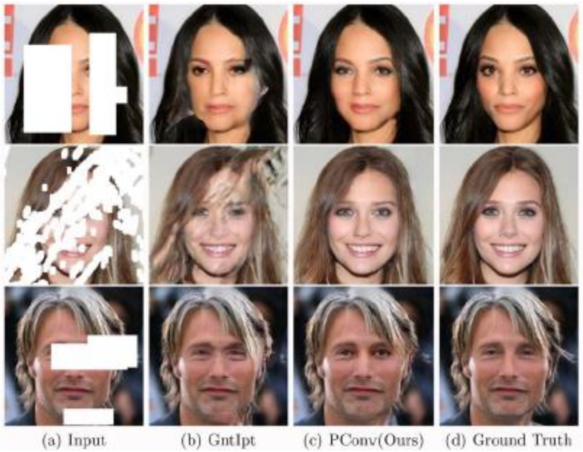
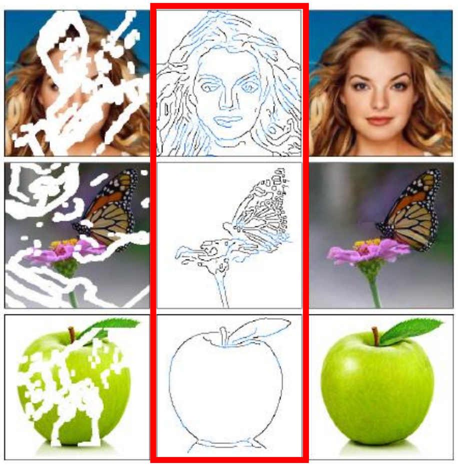


<기존 방법론>



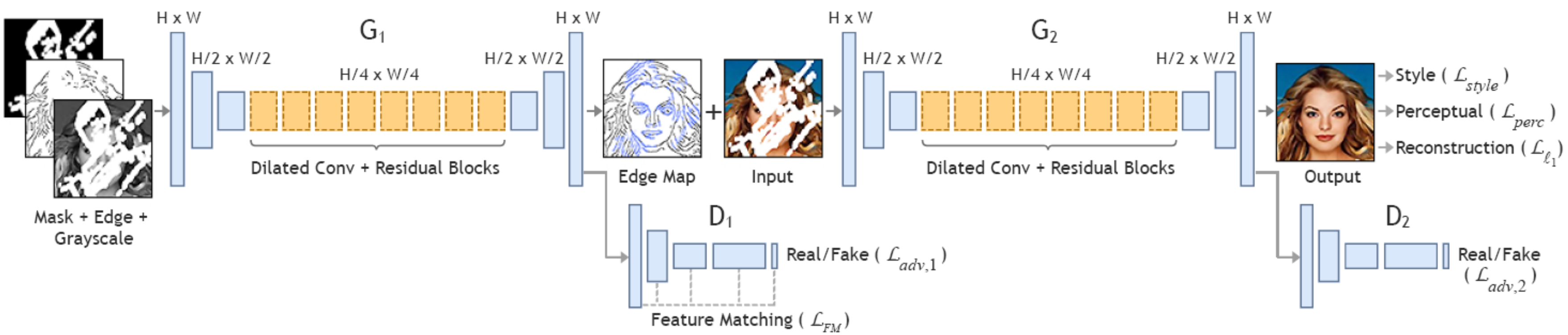
<제안 방법론>

1. Edge Connect Introduction

- Proposing Method Overview

- Sketches의 중요성을 강조하며 'lines first, color next' 접근법을 제안
- '**Edge Generator**' and '**Image Completion**'으로 나뉘는 two stage process로 구성되어 있음

<Edge Connect Model Architecture>

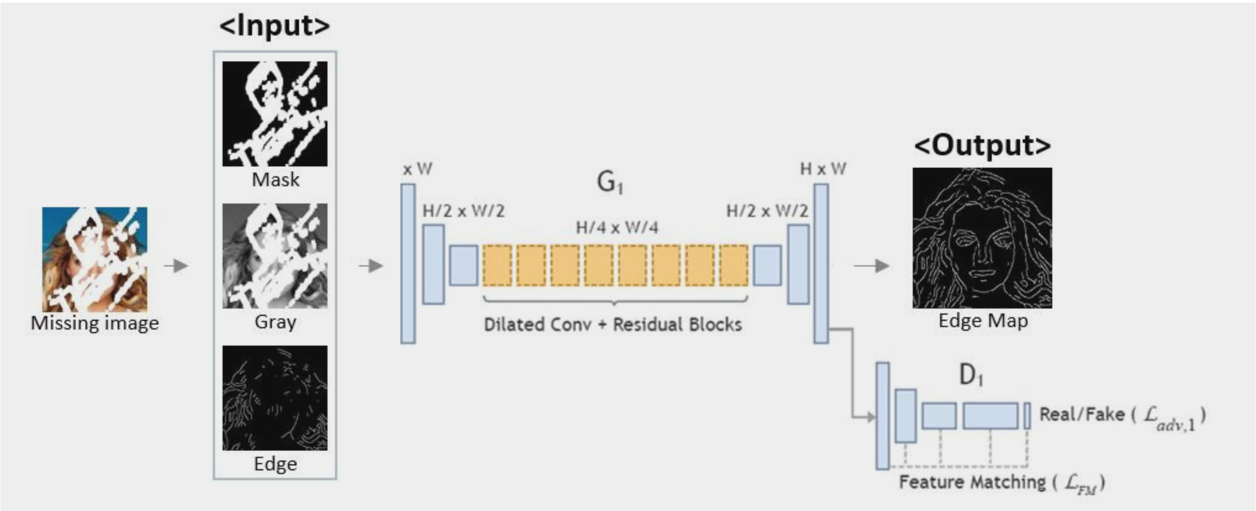


Edge Generator (G_1, D_1)

Image Completion Network (G_2, D_2)

2. Model Structure

< Edge Generator (G_1, D_1) >

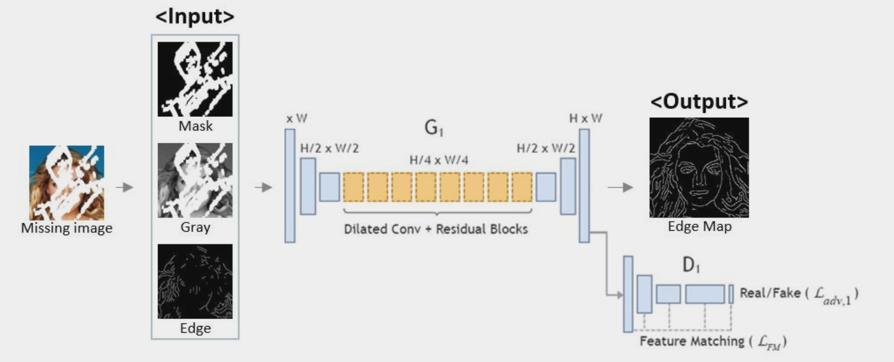


- Input & Output
  - ✓ $C_{pred} = G_1(M, \tilde{I}_{gray}, \tilde{C}_{gt})$
- Notation
  - ✓ Ground truth image, edge map, grayscale : I_{gt}, C_{gt}, I_{gray}
  - ✓ Mask : **M** (1 for the missing region, 0 for background)
  - ✓ Masked grayscale image : $\tilde{I}_{gray} = I_{gray} \odot (1 - M)$
  - ✓ Masked edge map : $\tilde{C}_{gt} = C_{gt} \odot (1 - M)$

  - 틸드가 붙은 Notation은 지워지지 않은 영역을 나타낸 것(Masked)

2. Model Structure

< Edge Generator (G_1, D_1) >



- Objective Function

$$\min_{G_1} \max_{D_1} \mathcal{L}_{G_1} = \min_{G_1} \left(\lambda_{adv,1} \max_{D_1} (\mathcal{L}_{adv,1}) + \lambda_{FM} \mathcal{L}_{FM} \right)$$

2. Model Structure

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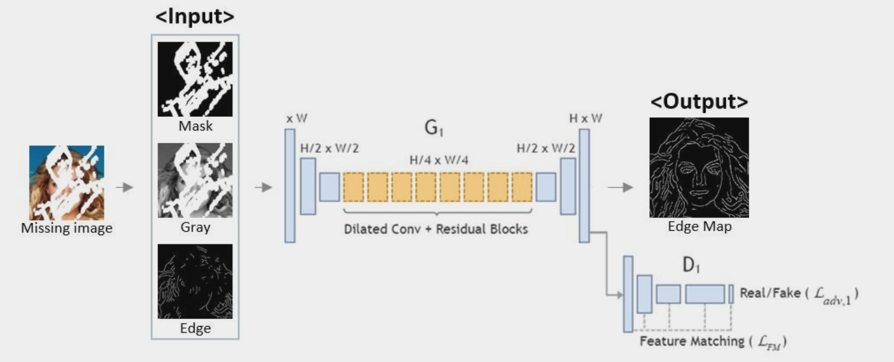
< Edge Generator (G_1, D_1) >



- Objective Function

$$\min_{G_1}\max_{D_1}\mathcal{L}_{G_1} = \min_{G_1}\left(\boxed{\lambda_{adv,1}\max_{D_1}(\mathcal{L}_{adv,1})} + \lambda_{FM}\mathcal{L}_{FM}\right)$$

➢ Adversarial Loss

$$\mathcal{L}_{adv,1} = \mathbb{E}_{(\mathbf{C}_{gt},\mathbf{I}_{gray})}\left[\log D_1(\mathbf{C}_{gt},\mathbf{I}_{gray})\right] + \mathbb{E}_{\mathbf{I}_{gray}}\log\left[1 - D_1(\mathbf{C}_{pred},\mathbf{I}_{gray})\right]$$

최대화↑

최대화↑

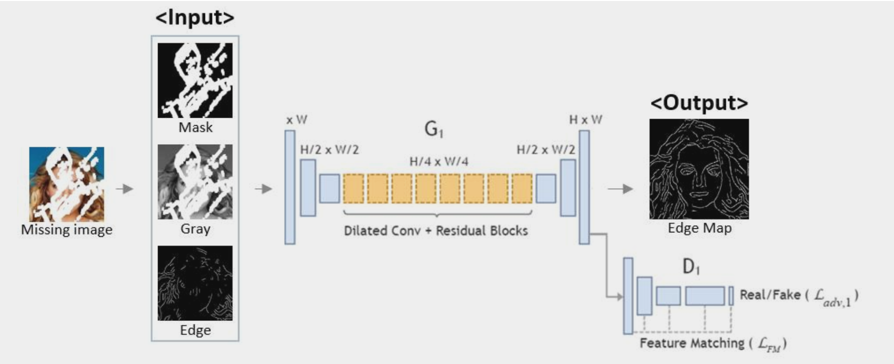
최소화↓

1에 가까워져야 하므로
GT는 real로 분류하도록

0에 가까워져야 하므로
Pred는 fake로 분류하도록

2. Model Structure

< Edge Generator (G_1, D_1) >



- Objective Function

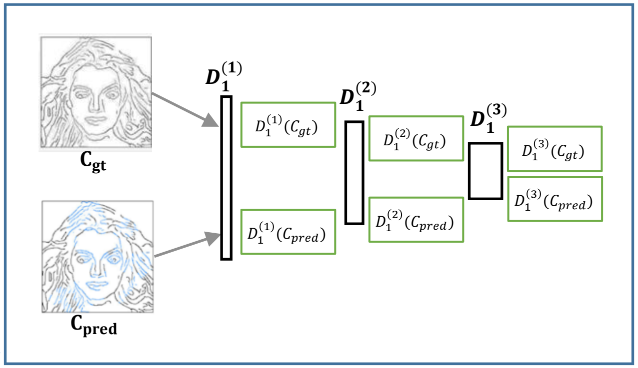
$$\min_{G_1}\max_{D_1}\mathcal{L}_{G_1} = \min_{G_1}\left(\lambda_{adv,1}\max_{D_1}(\mathcal{L}_{adv,1}) + \boxed{\lambda_{FM}\mathcal{L}_{FM}}\right)$$

➢ Feature-Matching Loss

$$\mathcal{L}_{FM} = \mathbb{E}\left[\sum_{i=1}^{L}\frac{1}{N_i}\underbrace{\left\|D_1^{(i)}(\mathbf{C}_{gt}) - D_1^{(i)}(\mathbf{C}_{pred})\right\|_1}_{\text{GT와 Pred가 유사해지도록}}\right]$$

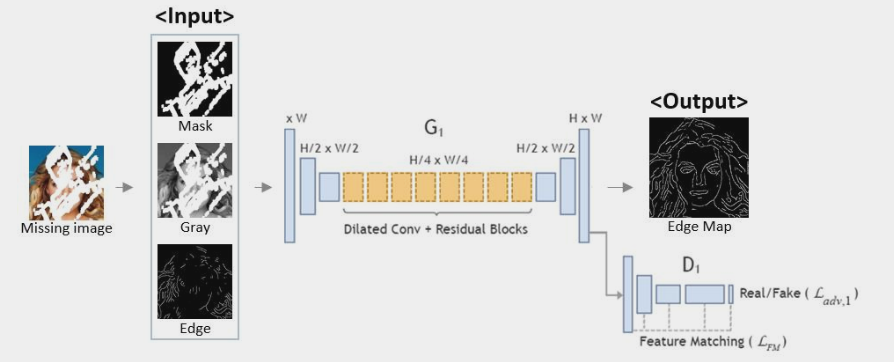
최소화↓

Discriminator의 Layer를 거친 Activation Map들을 각각 비교



2. Model Structure

< Edge Generator (G_1, D_1) >



- Objective Function

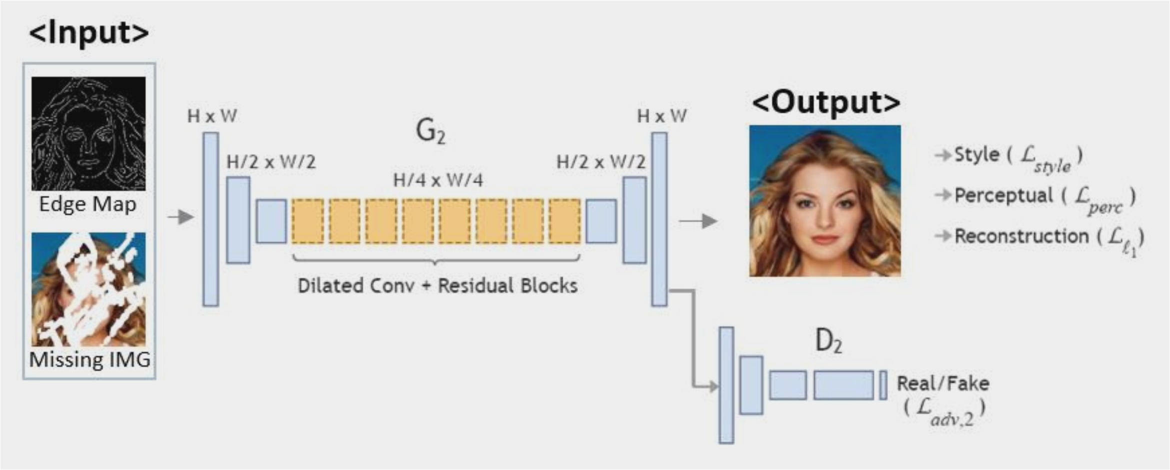
$$\min_{G_1} \max_{D_1} \mathcal{L}_{G_1} = \min_{G_1} \left(\lambda_{adv,1} \max_{D_1} (\mathcal{L}_{adv,1}) + \lambda_{FM} \mathcal{L}_{FM} \right)$$

✓ Regularization Parameter Setting

$\lambda_{adv,1}$ = 1

λ_{FM} = 10

< Image Completion Network (G_2, D_2) >



- Input & Output
  - ✓ $\mathbf{I_{pred}} = \mathbf{G_2}(\mathbf{\tilde{I}_{gt}}, \mathbf{C_{comp}})$

- Notation
  - ✓ **Comp**osite edge map : $\mathbf{C_{comp}} = \mathbf{C_{gt}} \odot (\mathbf{1} - \mathbf{M}) + \mathbf{C_{pred}} \odot \mathbf{M}$

2. Model Structure

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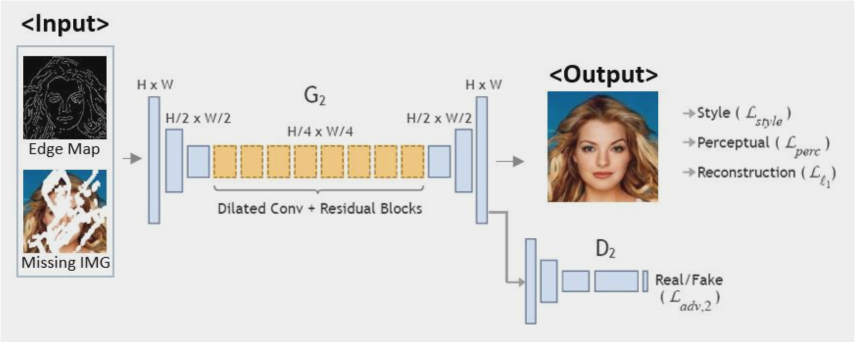
< Image Completion Network (G_2, D_2) >



- Loss Function

$$\mathcal{L}_{G_2} = \lambda_{\ell_1}\mathcal{L}_{\ell_1} + \lambda_{adv,2}\mathcal{L}_{adv,2} + \lambda_p\mathcal{L}_{perc} + \lambda_s\mathcal{L}_{style}$$

2. Model Structure

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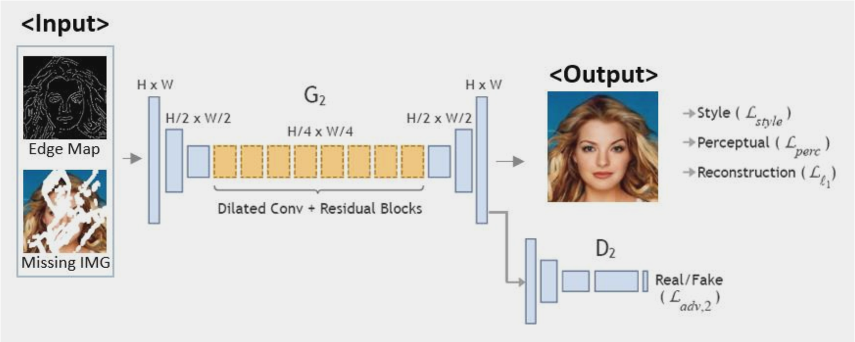
< Image Completion Network (G_2, D_2) >



- Loss Function

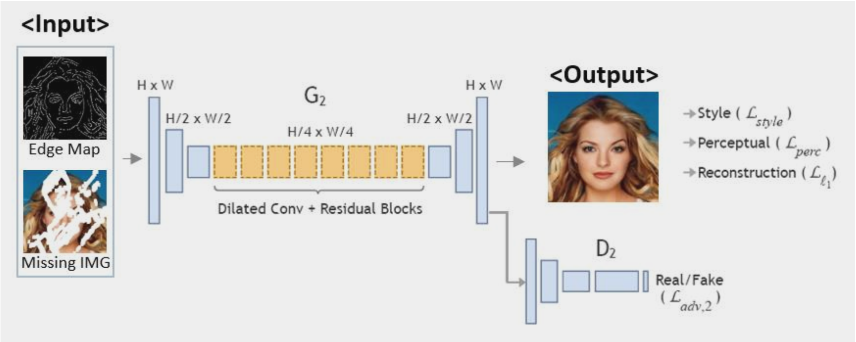
$$\mathcal{L}_{G_2} = \boxed{\lambda_{\ell_1}\mathcal{L}_{\ell_1}} + \lambda_{adv,2}\mathcal{L}_{adv,2} + \lambda_p\mathcal{L}_{perc} + \lambda_s\mathcal{L}_{style}$$

➢ L1 Loss

$$\mathcal{L}_{\ell_1} = \mathbb{E}\left(\left|\boldsymbol{I}_{\mathbf{gt}} - \boldsymbol{I}_{\boldsymbol{pred}}\right|\right)$$

2. Model Structure

< Image Completion Network (G_2, D_2) >



- Loss Function

$$\mathcal{L}_{G_2} = \lambda_{\ell_1}\mathcal{L}_{\ell_1} + \boxed{\lambda_{adv,2}\mathcal{L}_{adv,2}} + \lambda_p\mathcal{L}_{perc} + \lambda_s\mathcal{L}_{style}$$

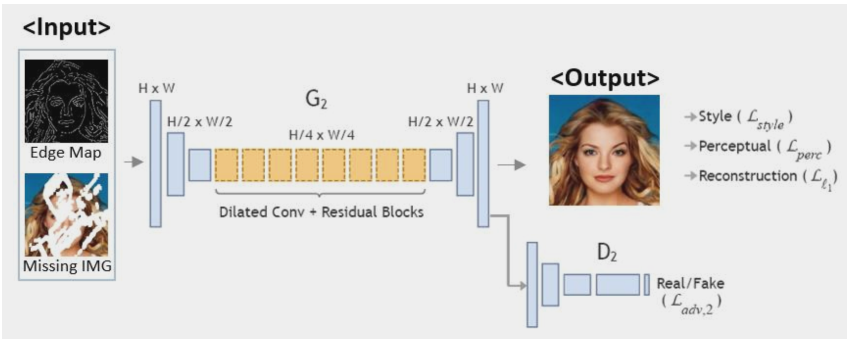
➢ Adversarial Loss

$$\mathcal{L}_{adv,2} = \mathbb{E}_{(\mathbf{I}_{gt},\mathbf{C}_{comp})}\left[\log D_2(\mathbf{I}_{gt},\mathbf{C}_{comp})\right] + \mathbb{E}_{\mathbf{C}_{comp}}\log\left[1 - D_2(\mathbf{I}_{pred},\mathbf{C}_{comp})\right]$$

Edge Generator의 Adversarial Loss와 유사하며,
Input만 완성 이미지(I_{gt}, I_{pred})로 변경

2. Model Structure

< Image Completion Network (G_2, D_2) >



- Loss Function

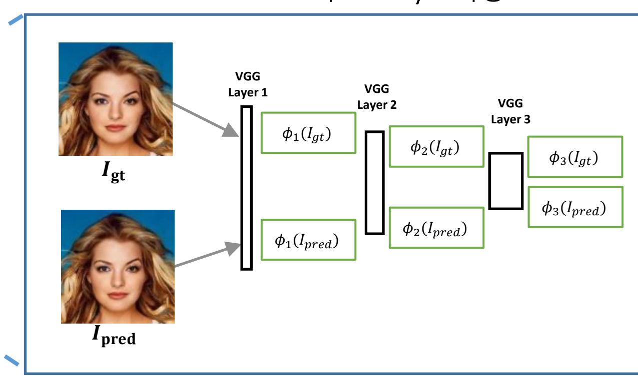
$$\mathcal{L}_{G_2} = \lambda_{\ell_1}\mathcal{L}_{\ell_1} + \lambda_{adv,2}\mathcal{L}_{adv,2} + \boxed{\lambda_p\mathcal{L}_{perc}} + \lambda_s\mathcal{L}_{style}$$

➢ Perceptual Loss

$$\mathcal{L}_{perc} = \mathbb{E}\left[\sum_i \frac{1}{N_i}\underline{\|\phi_i(\mathbf{I}_{gt}) - \phi_i(\mathbf{I}_{pred})\|_1}\right]$$

미리 학습해 놓은 다른 네트워크(VGG-19)를 활용해 얻은 Activation map 사이의 손실을 비교
(ϕ_i is the activation map of the i'th layer)

ImageNet dataset으로 Pre-train된 VGG-19의 1~5 Layer 사용



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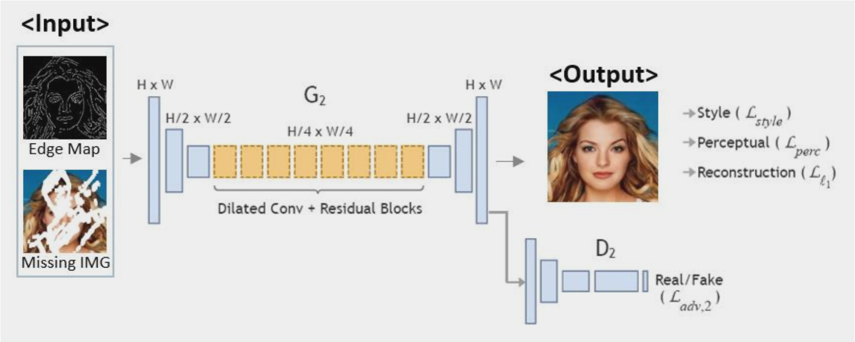

- Loss Function

$$\mathcal{L}_{G_2} = \lambda_{\ell_1}\mathcal{L}_{\ell_1} + \lambda_{adv,2}\mathcal{L}_{adv,2} + \lambda_p\mathcal{L}_{perc} + \boxed{\lambda_s\mathcal{L}_{style}}$$

➢ **Style Loss**

$$\mathcal{L}_{style} = \mathbb{E}_j\left[\|G_j^{\phi}(\tilde{\mathbf{I}}_{pred}) - G_j^{\phi}(\tilde{\mathbf{I}}_{gt})\|_1\right]$$

앞선 Perceptual Loss와 유사하게 Pred, GT를 VGG-19에 입력하여 나온
j'th Layer의 Activation map을 **Gram Matrix**로 변형하여 차이를 Loss로 사용

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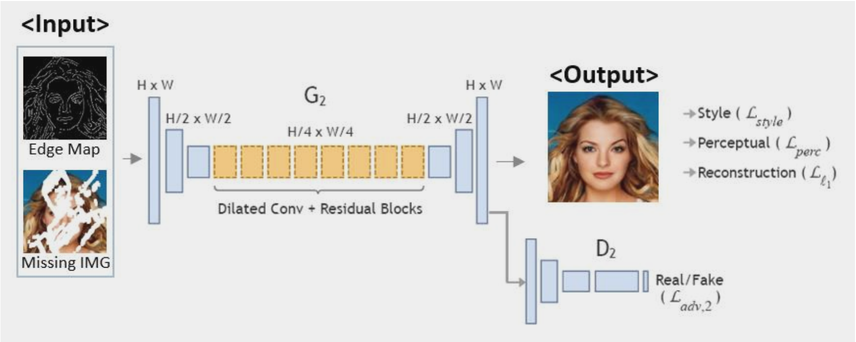
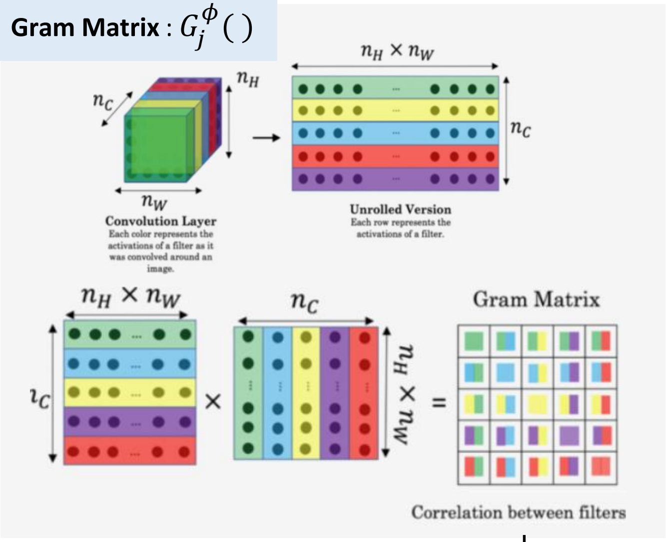


Gram Matrix : $G_j^{\phi}(\,)$



n_c X n_c 행렬은 해당 Activation map 안의 서로 다른 두 지점에 있는 특징들 간의 co-occurrence를 담고 있음.

- Loss Function

$$\mathcal{L}_{G_2} = \lambda_{\ell_1}\mathcal{L}_{\ell_1} + \lambda_{adv,2}\mathcal{L}_{adv,2} + \lambda_p\mathcal{L}_{perc} + \boxed{\lambda_s\mathcal{L}_{style}}$$

➢ Style Loss

$$\mathcal{L}_{style} = \mathbb{E}_j\left[\|G_j^{\phi}(\tilde{\mathbf{I}}_{pred}) - G_j^{\phi}(\tilde{\mathbf{I}}_{gt})\|_1\right]$$

앞선 Perceptual Loss와 유사하게 Pred, GT를 VGG-19에 입력하여 나온
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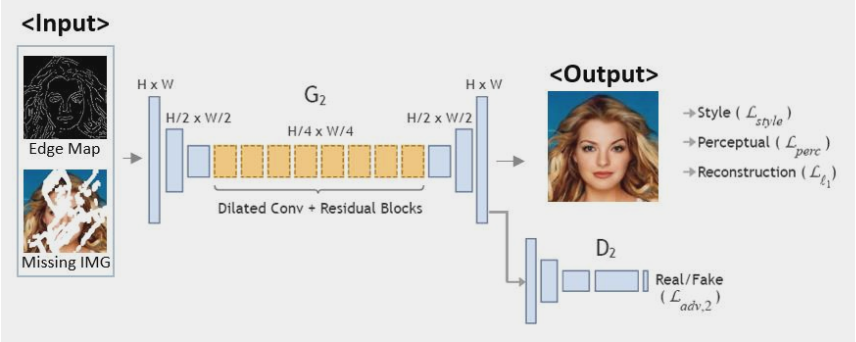

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$$\mathcal{L}_{G_2} = \lambda_{\ell_1}\mathcal{L}_{\ell_1} + \lambda_{adv,2}\mathcal{L}_{adv,2} + \lambda_p\mathcal{L}_{perc} + \lambda_s\mathcal{L}_{style}$$

✓ Regularization Parameter Setting

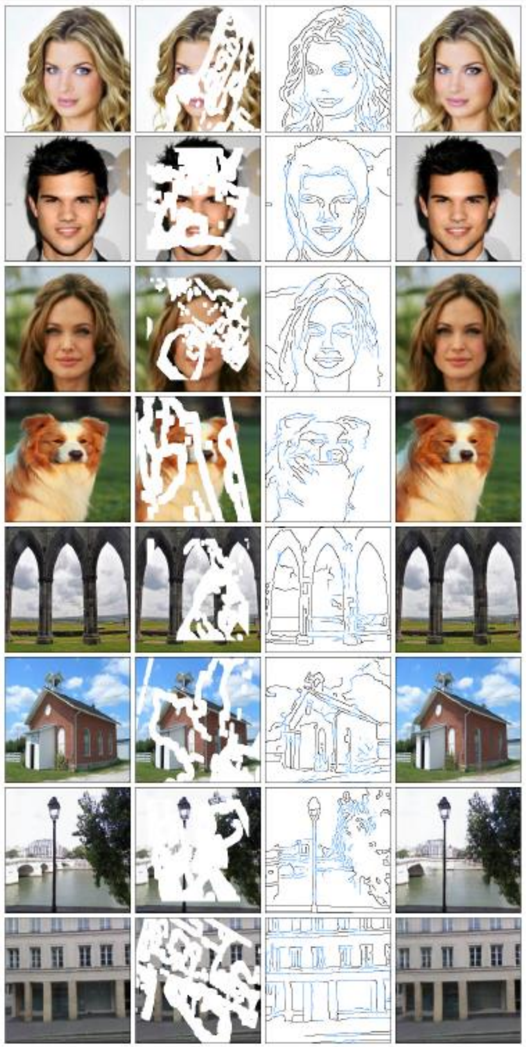
λ_{ℓ_1} = 1

$\lambda_{adv,2}$ = λ_p = 0.1

λ_s = 250

- **Experiments Setup**
  - Train & Test image size : 256 X 256
  - Canny edge detector 사용 ($\sigma \approx 2$)
  - Dataset : CelebA / Places2 / Paris StreetView
  - Baseline Models
    1) Contextual Attention (CA)
    2) Globally and Locally Consistent Image Completion (GLCIC)
    3) Partial Convolution (Pconv)
  - Evaluation Metrics
    1) Relative ℓ_1
    2) Structural Similarity Index (SSIM) : 시각적 화질 차이 및 유사도 측정 (휘도, 대비, 구조)
    3) Peak Signal-to-Noise Ratio (PSNR) : 최대신호대잡음비, 이미지 품질 측정
    4) Frechet Inception Distance (FID) : Feature space representation의 차이 측정

3. Experiments

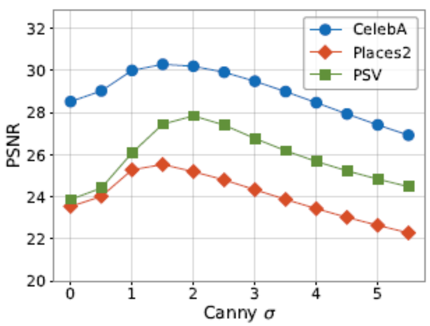


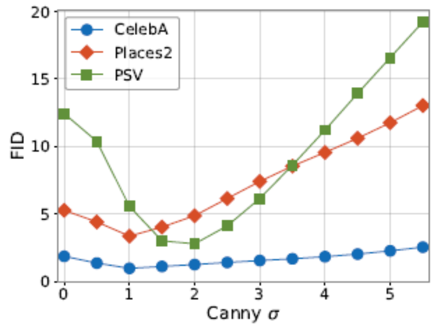
	Mask	CA	GLCIC	PConv*	Ours	Canny
ℓ_1 (%)†	10-20%	2.41	2.66	**1.14**	1.50	1.16
	20-30%	4.23	4.70	**1.98**	2.59	1.88
	30-40%	6.15	6.78	**3.02**	3.77	2.60
	40-50%	8.03	8.85	**4.11**	5.14	3.41
	Fixed	4.37	4.12	-	**3.86**	2.22
SSIM*	10-20%	0.893	0.862	0.869	**0.920**	0.941
	20-30%	0.815	0.771	0.777	**0.861**	0.902
	30-40%	0.739	0.686	0.685	**0.799**	0.863
	40-50%	0.662	0.603	0.589	**0.731**	0.821
	Fixed	0.818	0.814	-	**0.823**	0.892
PSNR*	10-20%	24.36	23.49	**28.02**	27.95	30.85
	20-30%	21.19	20.45	24.90	**24.92**	28.35
	30-40%	19.13	18.50	22.45	**22.84**	26.66
	40-50%	17.75	17.17	20.86	**21.16**	25.20
	Fixed	20.65	21.34	-	**21.75**	26.52
FID†	10-20%	6.16	11.84	-	**2.32**	2.25
	20-30%	14.17	25.11	-	**4.91**	3.42
	30-40%	24.16	39.88	-	**8.91**	4.87
	40-50%	35.78	54.30	-	**14.98**	7.13
	Fixed	8.31	8.42	-	**8.16**	3.24

3. Experiments

▪ Edge Detection 관련 실험

- Effect of σ in Canny Edge Detctor





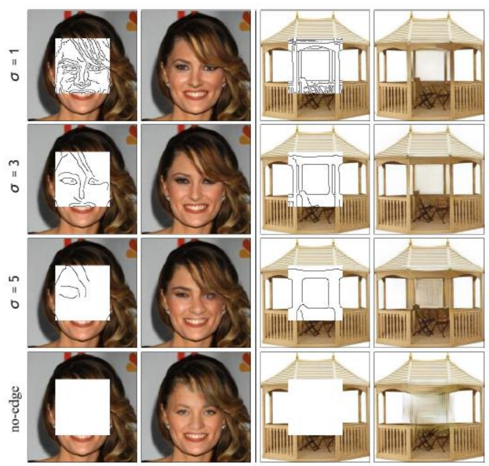


Figure 7: Effect of σ in Canny edge detector on inpainting results. Top to bottom: $\sigma = 1, 3, 5$, no edge data.

- Alternative Edge Detection Systems

1) Canny Edge Detector : speed, robustness, ease of use
2) Holistically-nested Edge Detector(HED)
   > NN 기반, Noise 적음, 윤곽선 위주
3) Element-wise multiplication

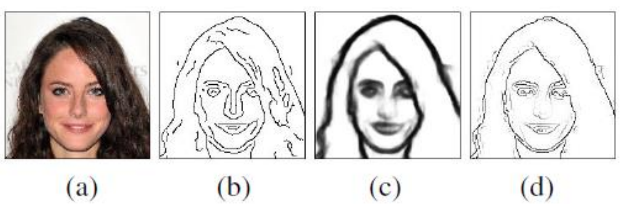
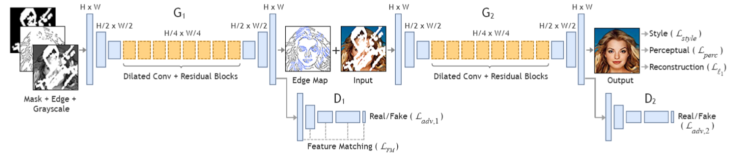
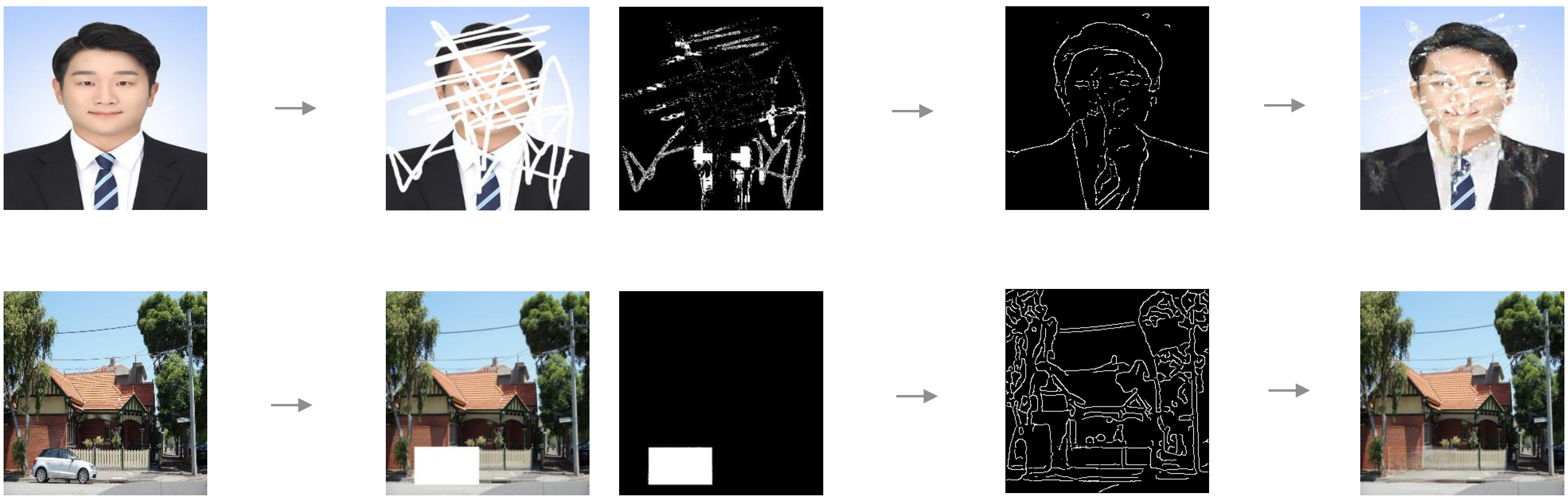


Figure 8: (a) Image. (b) Canny. (c) HED. (d) Canny$\odot$HED.

3. Experiments

- **Custom Data Test**





원본 이미지

Input

Edge Generator Result

Image Completion Result

감사합니다!