Stylization

2019~2020 논문 구조 요약

201810977 이정인

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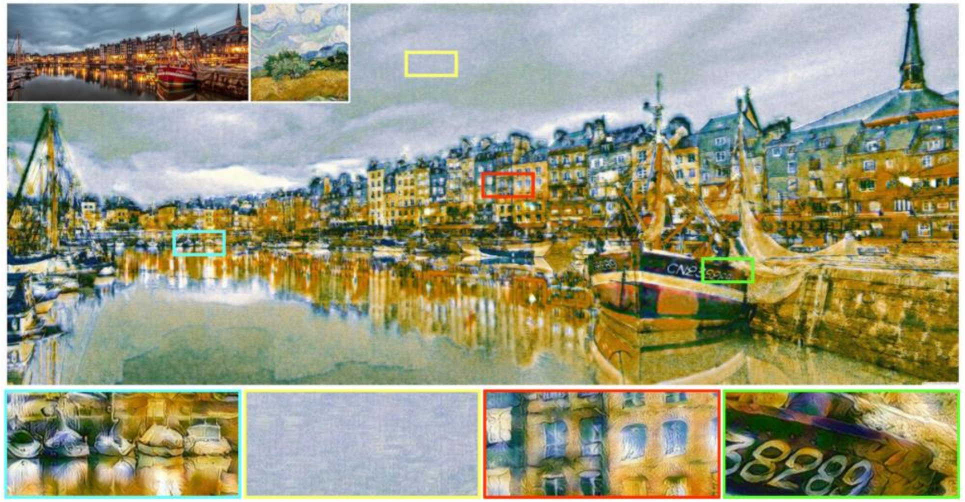
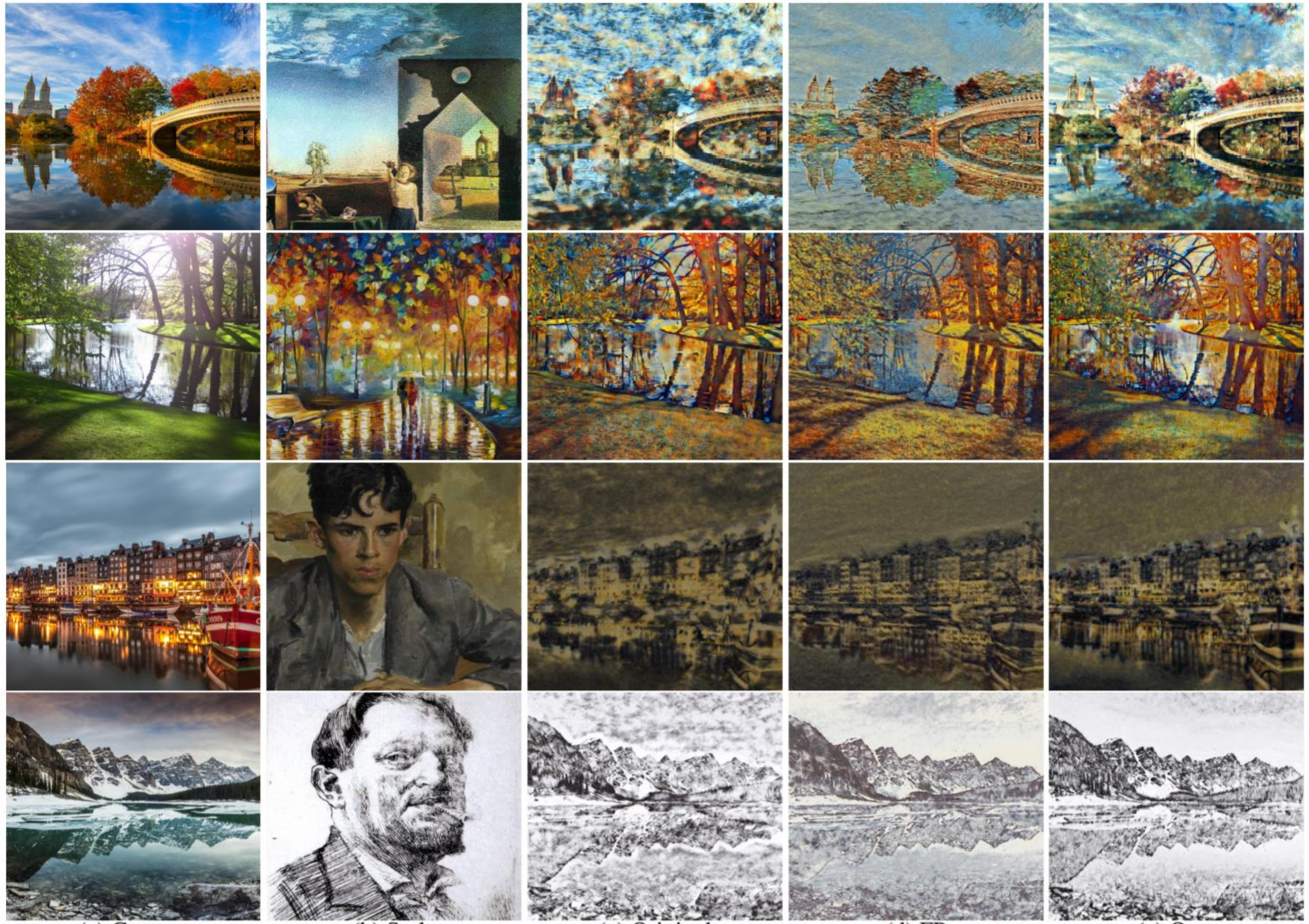
01 Collaborative Distillation for Ultra-Resolution Universal Style Transfer

Huan Wang, Yijun Li, Yuehai Wang, Haoji Hu, Ming-Hsuan Yang, CVPR, 2020

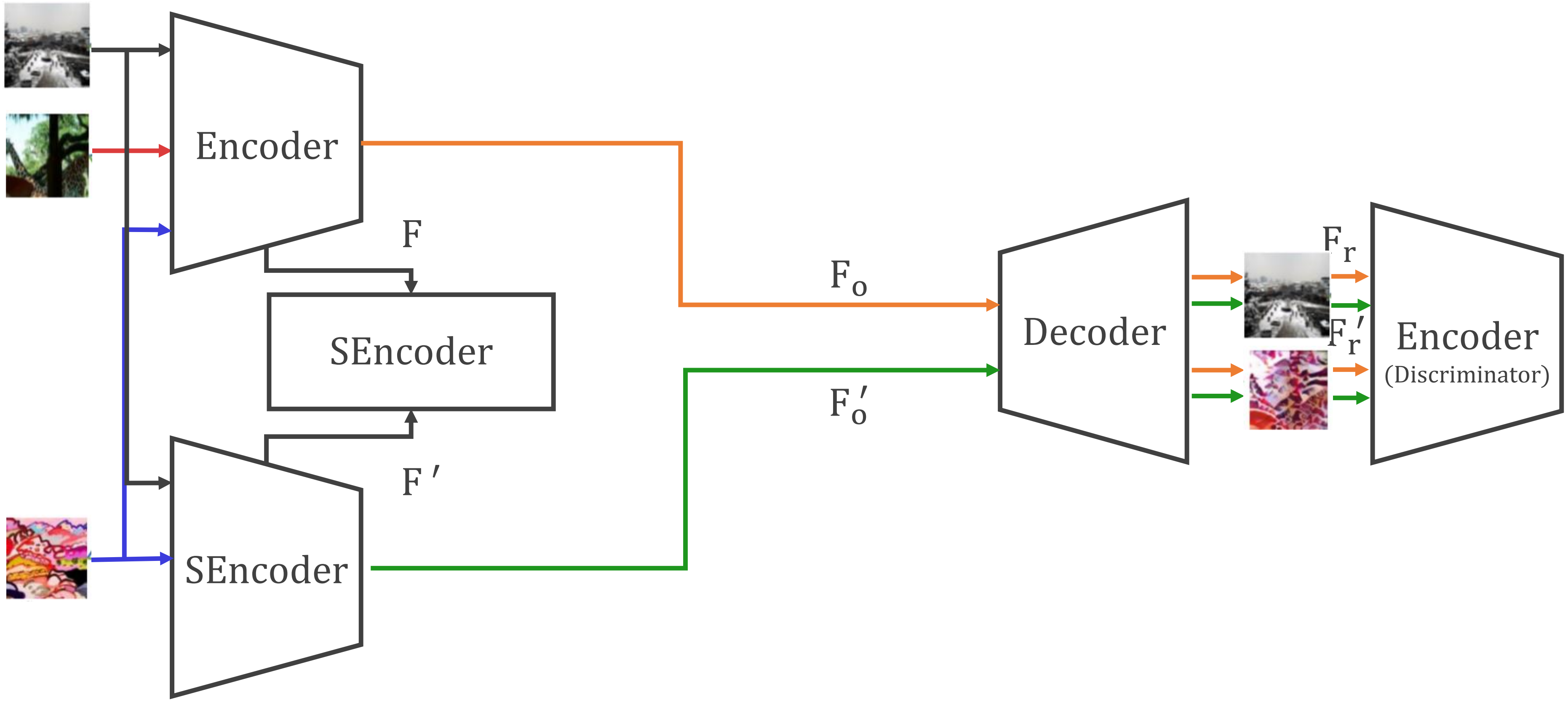




(a) Content (b) Style (c) Original (d) FP (e) Ours

01 Collaborative Distillation for Ultra-Resolution Universal Style Transfer

Huan Wang, Yijun Li, Yuehai Wang, Haoji Hu, Ming-Hsuan Yang, CVPR, 2020



SEncoder : model의 크기를 줄인 Small Encoder, 수용할 수 있는 해상도를 크게 하여 고해상도의 스타일 변환을 시도

01 Collaborative Distillation for Ultra-Resolution Universal Style Transfer

Huan Wang, Yijun Li, Yuehai Wang, Haoji Hu, Ming-Hsuan Yang, CVPR, 2020

$$\boxed{L_{total} = \beta \sum_{i=1}^{k} L_{embed} + L_{collab}}$$

L_{embed} : feature domain information (for small encoder)

L_{collab} : for image reconstruction

01 Collaborative Distillation for Ultra-Resolution Universal Style Transfer

Huan Wang, Yijun Li, Yuehai Wang, Haoji Hu, Ming-Hsuan Yang, CVPR, 2020

$$L_{total} = \beta \sum_{i=1}^{k} L_{embed} + L_{collab}$$

$$\mathcal{L}_r^{(k)} = \|\mathcal{I}_r - \mathcal{I}_o\|_2^2 + \lambda_p \sum_{i=1}^{k} \|\mathcal{F}_r^{(i)} - \mathcal{F}_o^{(i)}\|_2^2, \quad (1)$$

$$\mathcal{L}_{\text{st}} = \|\mathcal{F}_{\text{st}}^{(4)} - \mathcal{F}_c^{(4)}\|_2^2 + \lambda_s \sum_{i=1}^{4} \|\mathcal{G}_{\text{st}}^{(i)} - \mathcal{G}_s^{(i)}\|_2^2, \quad (2)$$

$$\mathcal{G} = \mathcal{F} \cdot \mathcal{F}^T, \quad (3)$$

$$\mathcal{F} = Q \cdot \mathcal{F}', \quad (4)$$

$$\mathcal{L}_{\text{embed}} = \|\mathcal{F} - Q \cdot \mathcal{F}'\|_2^2. \quad (5)$$

Huan Wang, Yijun Li, Yuehai Wang, Haoji Hu, Ming-Hsuan Yang, CVPR, 2020

01 Collaborative Distillation for Ultra-Resolution Universal Style Transfer

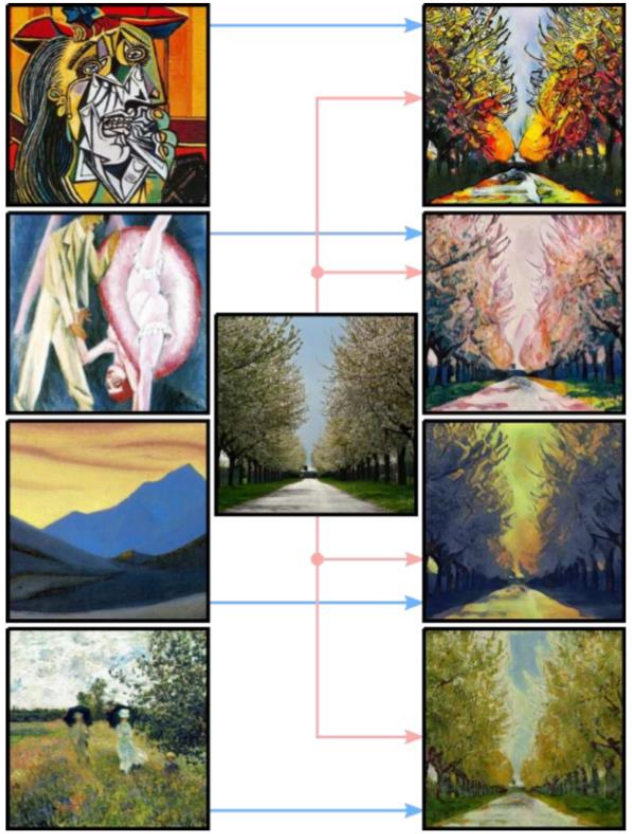
Huan Wang, Yijun Li, Yuehai Wang, Haoji Hu, Ming-Hsuan Yang, CVPR, 2020

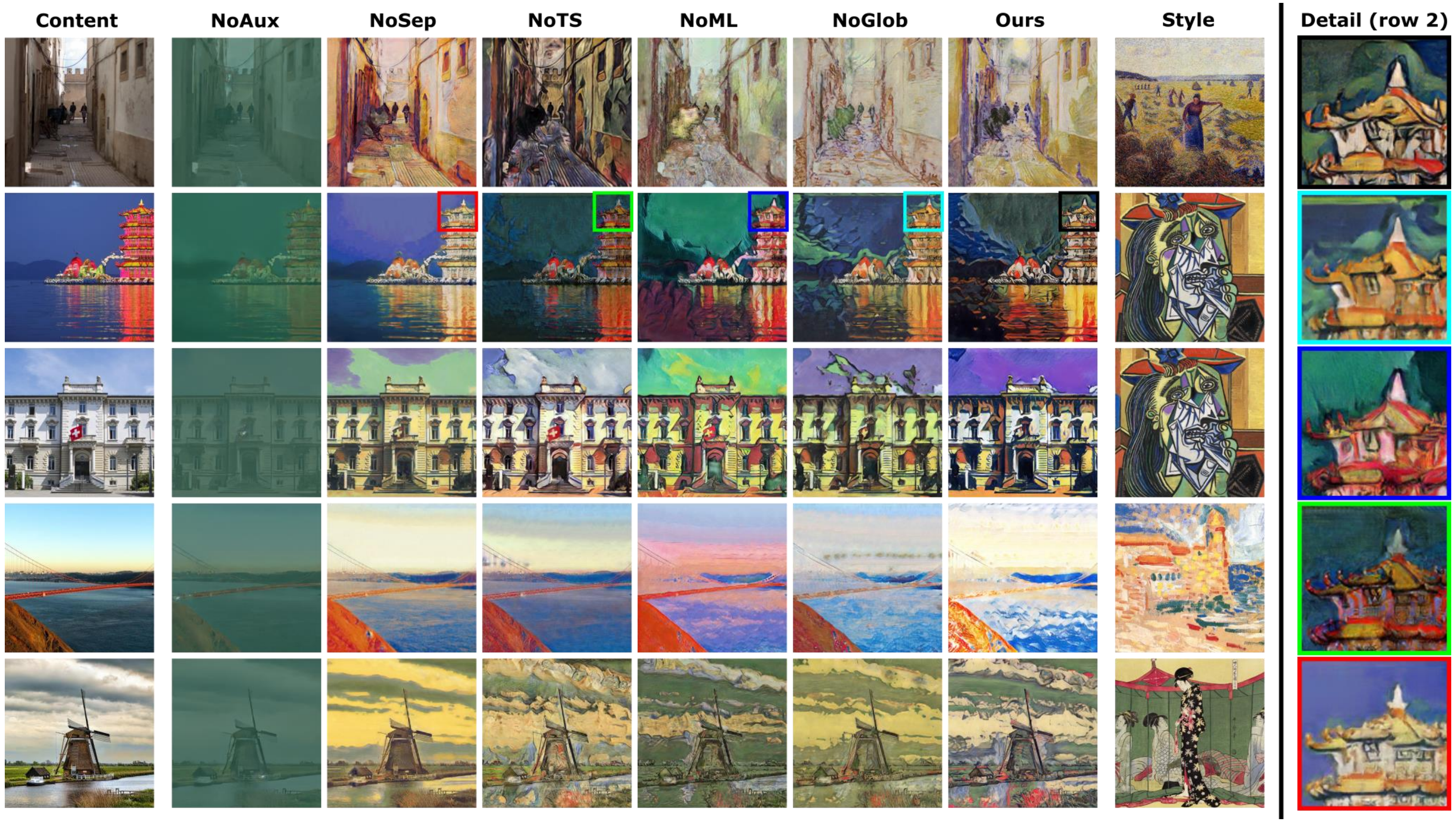
2차 피드백 내용

Q. embed, collab loss의 차이점
A. embed는 sencoder를 만들기 위해 존재(feat loss), collab은 encoder를 만들기 위해 존재(rec loss)

02 Two-Stage Peer-Regularized Feature Recombination for Arbitrary Image Style Transfer

Jan Svoboda, Asha Anoosheh, Christian Osendorfer, Jonathan Masci, CVPR, 2020





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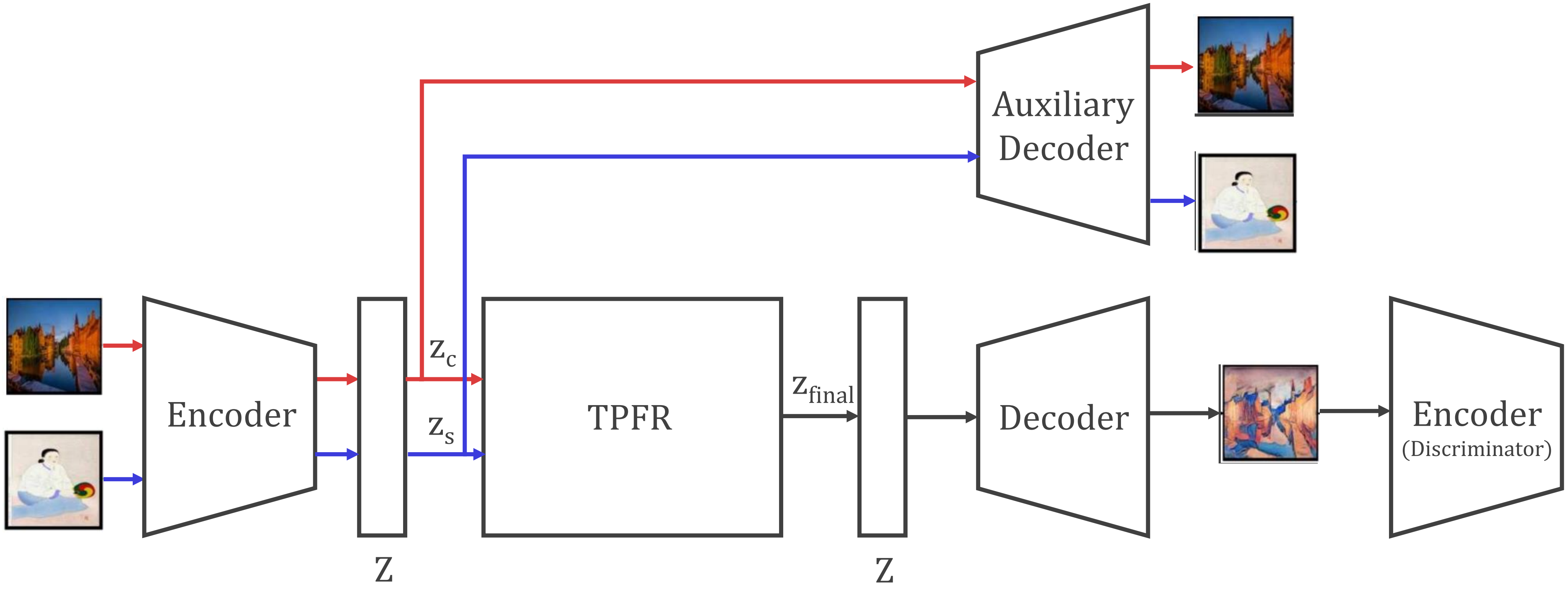


TPFR : latent space에서 효과적으로 style transfer 하기 위해 사용하는 모듈, input pixel이 어떤 style과 가장 가까운 지 매칭하기 위해 k-NN graph를 사용하고 recombination으로 각각의 mapping에 따라 style를 강화시켜 도출 된 latent의 style이 decoder의 입력으로 사용됨

02

Two-Stage Peer-Regularized Feature Recombination for Arbitrary Image Style Transfer

Jan Svoboda, Asha Anoosheh, Christian Osendorfer, Jonathan Masci, CVPR, 2020

$$L_{total} = L_C + L_D + L_{\widetilde{D}}$$

L_C : Discriminator

L_D : Main decoder

$L_{\widetilde{D}}$: Auxiliary decoder

02 Two-Stage Peer-Regularized Feature Recombination for Arbitrary Image Style Transfer

Jan Svoboda, Asha Anoosheh, Christian Osendorfer, Jonathan Masci, CVPR, 2020

$$L_{total} = L_C + L_D + L_{\tilde{D}}$$
$$L_{\tilde{D}} = L_{z_{style}} + \tilde{L}_{z_{style}} + \tilde{L}_{z_{style}}$$

$$\begin{aligned} L_{z_{cont}} &= f[E(D(T(z_i, z_t)))_C - (z_i)_C] \\ &+ f[E(D(T(z_i, z_i)))_C - (z_i)_C] \end{aligned} \quad (2)$$

Content feature cycle loss

$$\begin{aligned} L^{pos}_{z_{style}} &= f[(z_{i_1})_S - (z_{i_2})_S] + f[(z_{t_1})_S - (z_{t_2})_S] \\ L^{neg}_{z_{style}} &= f[(z_{i_1})_S - (z_{t_1})_S] + f[(z_{i_2})_S - (z_{t_2})_S] \\ L_{z_{style}} &= L^{pos}_{z_{style}} + max(0.0, \mu - L^{neg}_{z_{style}}). \end{aligned} \quad (3)$$

Metric learning loss : latent의 style part에 clustering을 적용하기 위해 사용된다.
Posivite loss에서는 첫번째 latent와 두번째 latent의 style part가 유사해지길 원하며(결과적으로 지향)
Negatice loss에서는 latent가 자신의 본래 style part와 유사해지길 원한다. (결과적으로 지양)

$$\tilde{L}_{idt} = f[\tilde{D}(E(x_i)) - x_i] + f[\tilde{D}(E(x_t)) - x_t]. \quad (4)$$

Classical reconstruction loss : 오토인코더에서 주로 사용하는 reconstruction loss

$$\tilde{L}_{z_{cycle}} = f[E(\tilde{D}(z_i)) - (z_i)] + f[E(\tilde{D}(z_t)) - (z_t)], \quad (5)$$

Latent cycle loss
: 입력 이미지의 latent code와 그 이미지의 reconstruction 의 latent code 차이

02 Two-Stage Peer-Regularized Feature Recombination for Arbitrary Image Style Transfer

Jan Svoboda, Asha Anoosheh, Christian Osendorfer, Jonathan Masci, CVPR, 2020

$$L_{total} = L_C + L_D + L_{\tilde{D}}$$
$$L_D = L_{gen} + L_{z_{transf}} + \lambda L_{idt}$$

$$L_{gen} = \mathbb{E}_{x_i \sim \mathbb{P}}\left[\left(C(x_i) - \mathbb{E}_{x_f \sim \mathbb{Q}} C(x_f) + 1\right)^2\right] + \mathbb{E}_{x_f \sim \mathbb{Q}}\left[\left(\mathbb{E}_{x_i \sim \mathbb{P}} C(x_i) - C(x_f) + 1\right)^2\right], \quad (7)$$

Decoder adversarial loss
- P : 실제 데이터의 분포
- Q : 생성된 데이터의 분포(fake)
- C : discriminator

$$L_{z_{transf}} = f[E(D(T(z_i, z_t)))_C - (z_i)_C] + f[E(D(T(z_i, z_t)))_S - (z_t)_S]. \quad (8)$$

Transfer latent cycle loss : 스타일화 된 이미지의 Iinput contet와 target style을 적절히 recombining(재결합) 하여 나타내기 위해 사용

$$L_{idt} = f[D(T(z_i, z_i)) - x_i] + f[D(T(z_t, z_t)) - x_t]. \quad (9)$$

Classical reconstruction loss

02 Two-Stage Peer-Regularized Feature Recombination for Arbitrary Image Style Transfer

Jan Svoboda, Asha Anoosheh, Christian Osendorfer, Jonathan Masci, CVPR, 2020

$$L_{total} = L_C + L_D + L_{\widetilde{D}}$$
$$L_C$$

$$\begin{aligned} L_C = \; & \mathbb{E}_{x_i \sim \mathbb{P}} \left[\left(C\left(x_i\right) - \mathbb{E}_{x_f \sim \mathbb{Q}} C\left(x_f\right) - 1 \right)^2 \right] \\ & + \mathbb{E}_{x_f \sim \mathbb{Q}} \left[\left(\mathbb{E}_{x_i \sim \mathbb{P}} C\left(x_i\right) - C\left(x_f\right) - 1 \right)^2 \right]. \end{aligned} \tag{11}$$

C : discriminator

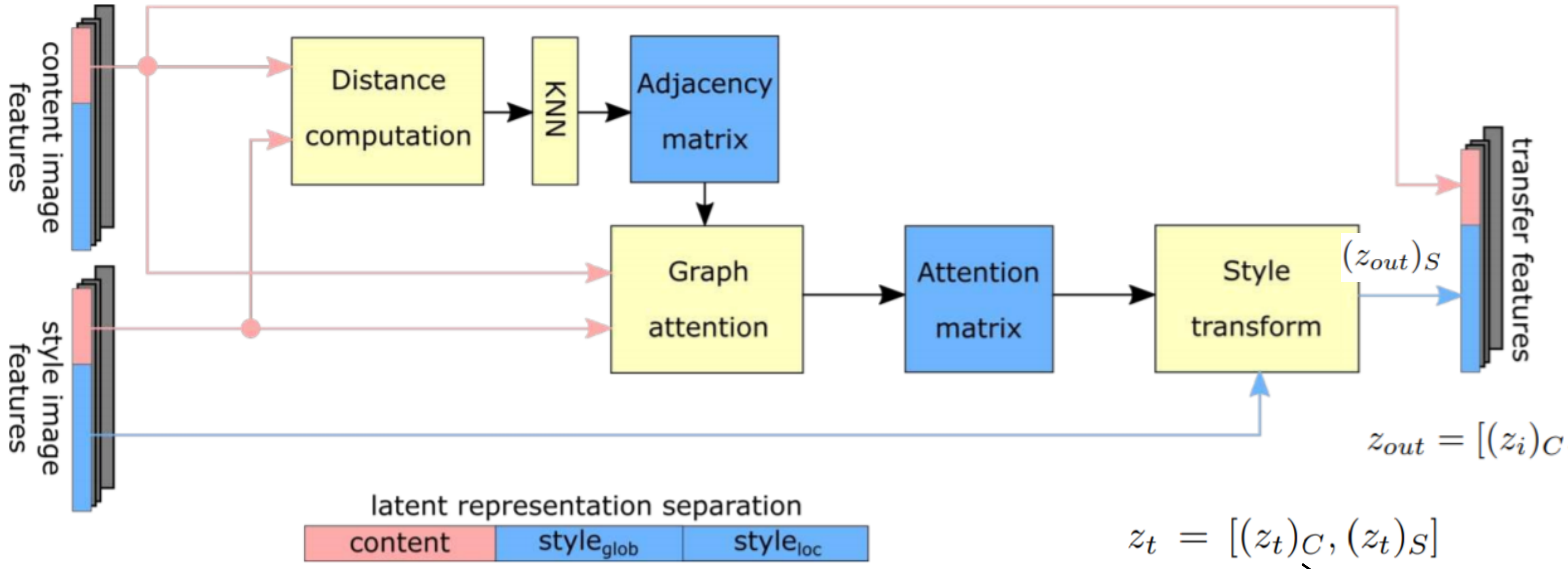
실제 이미지에 대한 판별 결과와(1에 가까움)
가짜 이미지에 대한 판별 결과의 차이를 구함(1에 가까울수록 좋음)

02 Two-Stage Peer-Regularized Feature Recombination for Arbitrary Image Style Transfer

Jan Svoboda, Asha Anoosheh, Christian Osendorfer, Jonathan Masci, CVPR, 2020

2차 피드백 내용

Q. Z_{final} ?
A.



$$z_{out} = [(z_i)_C, (z_{out})_S].$$

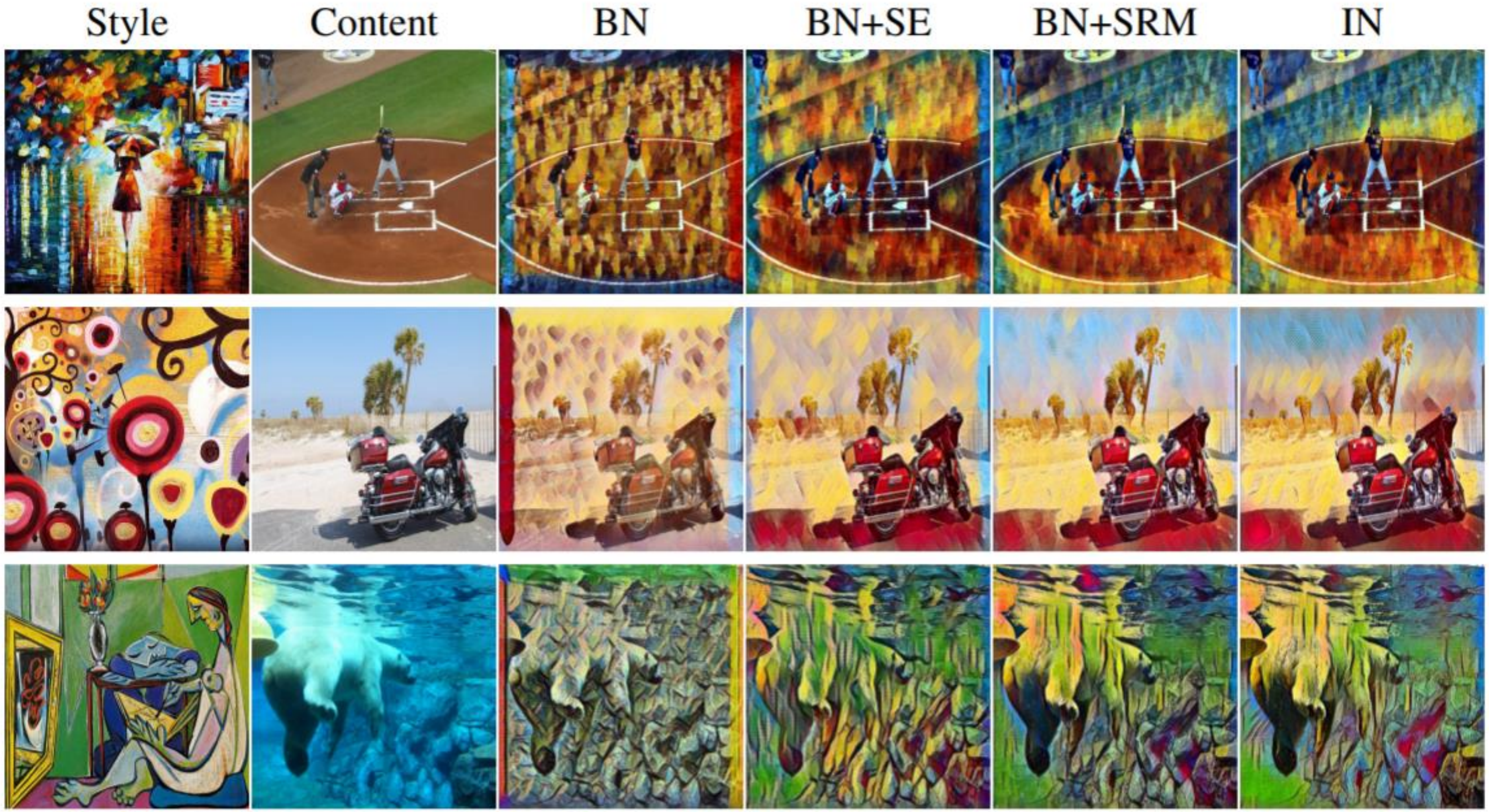
$$z_t = [(z_t)_C, (z_t)_S]$$

$$(z_{out})_S$$

$$z_{final} = [(z_{final})_C, (z_{out})_S]$$

03 SRM: A Style-Based Recalibration Module for Convolutional Neural Networks

HyunJae Lee, Hyo-Eun Kim, Hyeonseob Nam, ICCV, 2019



03

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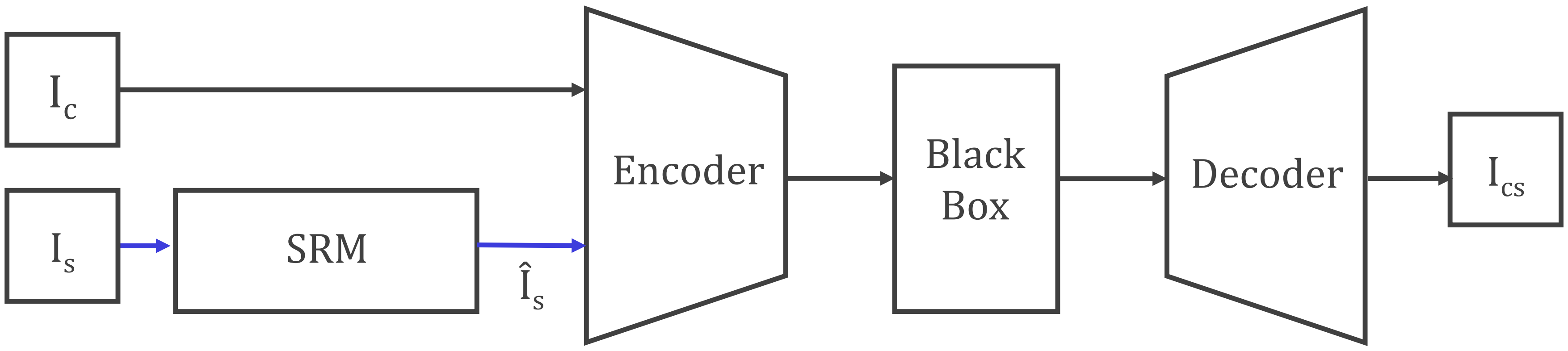
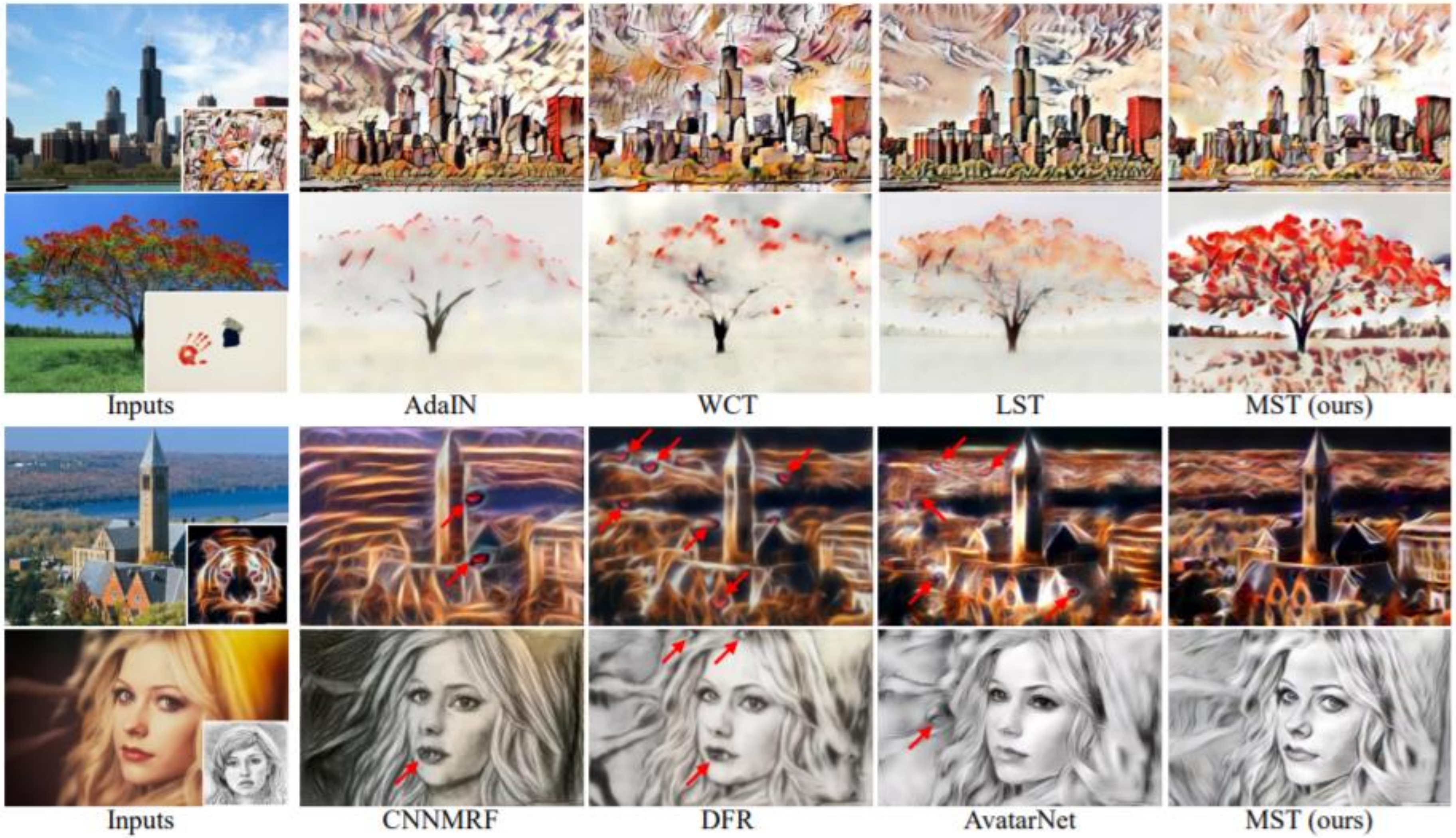
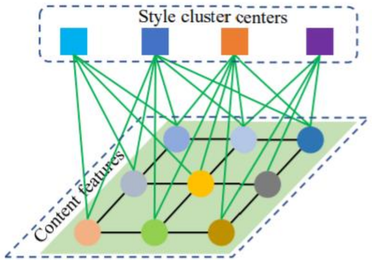


04 Multimodal Style Transfer via Graph Cuts

Yulun Zhang, Chen Fang, Yilin Wang, Zhaowen Wang, Zhe Lin, Yun Fu, Jimei Yang, ICCV, 2019





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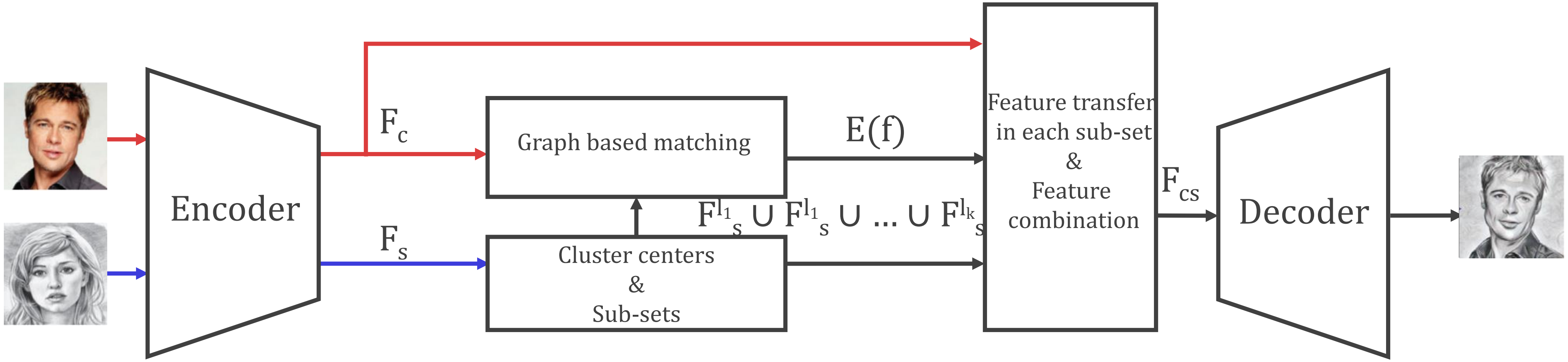


Graph based matching : 라벨이 붙은 subset과 content feature를 매칭시킴
Cluster centers & Subset : style feature를 cluster center 방식을 통해 subset 으로 나누어 라벨을 부여함
Feature transfer & combination : 각각의 style 에 따라 content 를 subset 으로 분리하고 결합하여 content style feature 를 생성함

04 Multimodal Style Transfer via Graph Cuts

Yulun Zhang, Chen Fang, Yilin Wang, Zhaowen Wang, Zhe Lin, Yun Fu, Jimei Yang, ICCV, 2019

$$\boxed{L_{total} = l_C + \gamma l_S}$$

l_C : Content loss

l_S : Style loss

04 Multimodal Style Transfer via Graph Cuts

Yulun Zhang, Chen Fang, Yilin Wang, Zhaowen Wang, Zhe Lin, Yun Fu, Jimei Yang, ICCV, 2019

$$\boxed{L_{total} = l_C + \gamma l_S}$$

$$l_c = \left\| \phi_{4\_1}\left(I_c\right) - \phi_{4\_1}\left(I_{cs}\right) \right\|_2 , \qquad (11)$$

→ φ4_1 (·) : Conv_4_1에서 추출한 feature

$$l_s = \sum_{i=1}^{4} \left(\left\| \mu\left(\phi_{i\_1}\left(I_s\right)\right) - \mu\left(\phi_{i\_1}\left(I_{cs}\right)\right) \right\|_2 \right) + \sum_{i=1}^{4} \left(\left\| \sigma\left(\phi_{i\_1}\left(I_s\right)\right) - \sigma\left(\phi_{i\_1}\left(I_{cs}\right)\right) \right\|_2 \right) , \qquad (12)$$

→ φi_1 (·) : Conv_i_1에서 추출한 feature

04 Multimodal Style Transfer via Graph Cuts

Yulun Zhang, Chen Fang, Yilin Wang, Zhaowen Wang, Zhe Lin, Yun Fu, Jimei Yang, ICCV, 2019

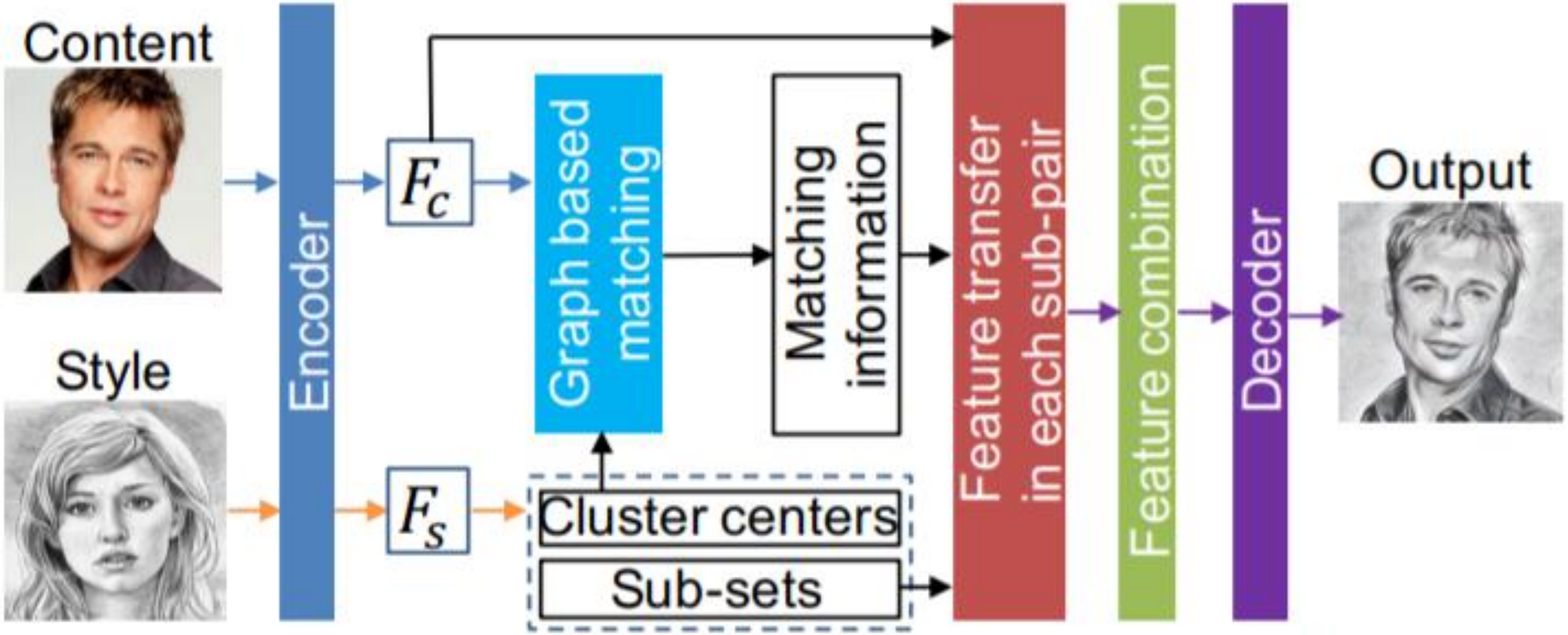


Figure 3: An overview of our MST algorithm.

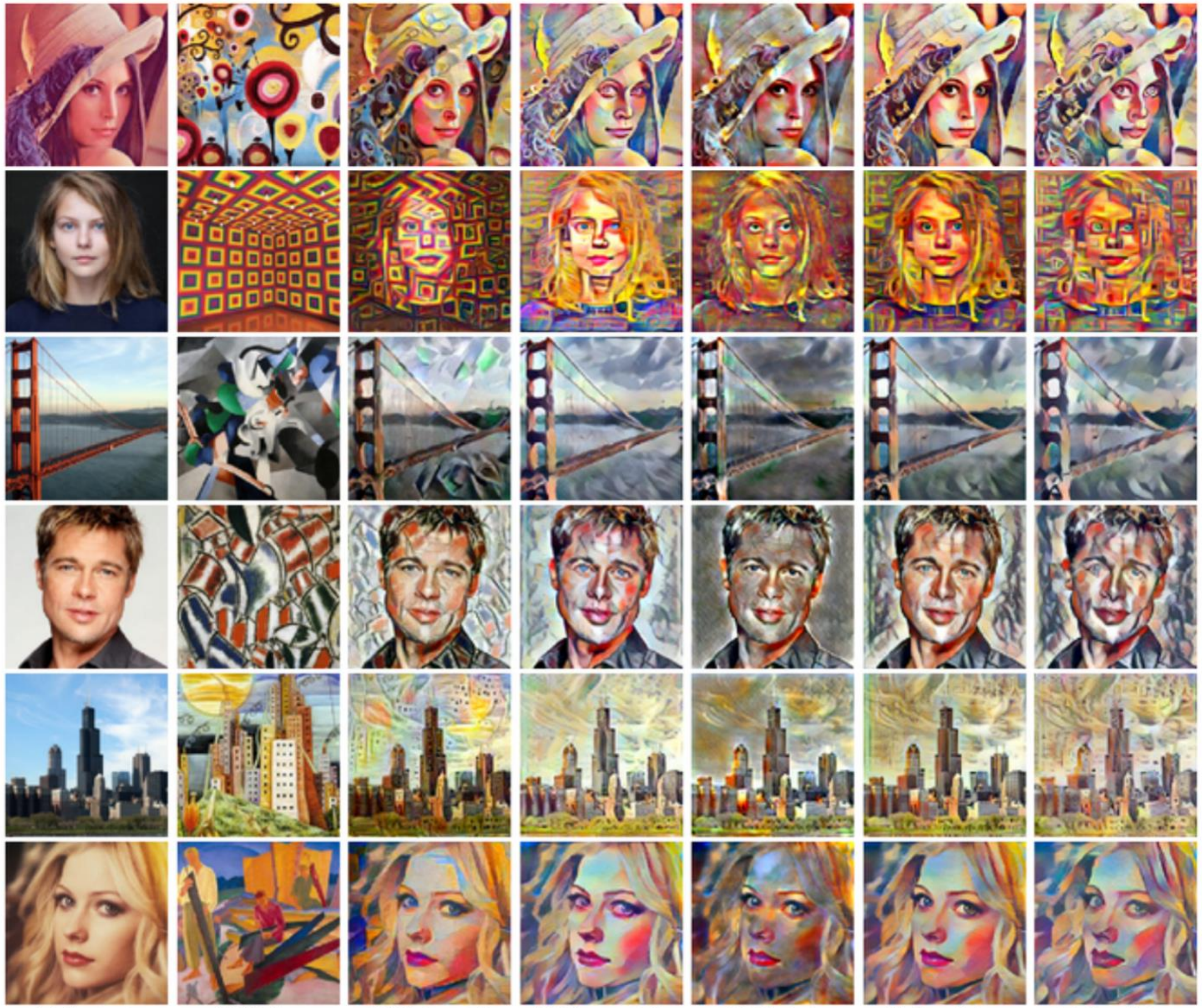
2차 피드백 내용

Q. 무엇으로 Clustering을 하나?
A. style feature

05

Total Style Transfer With A Single Feed-forward Network

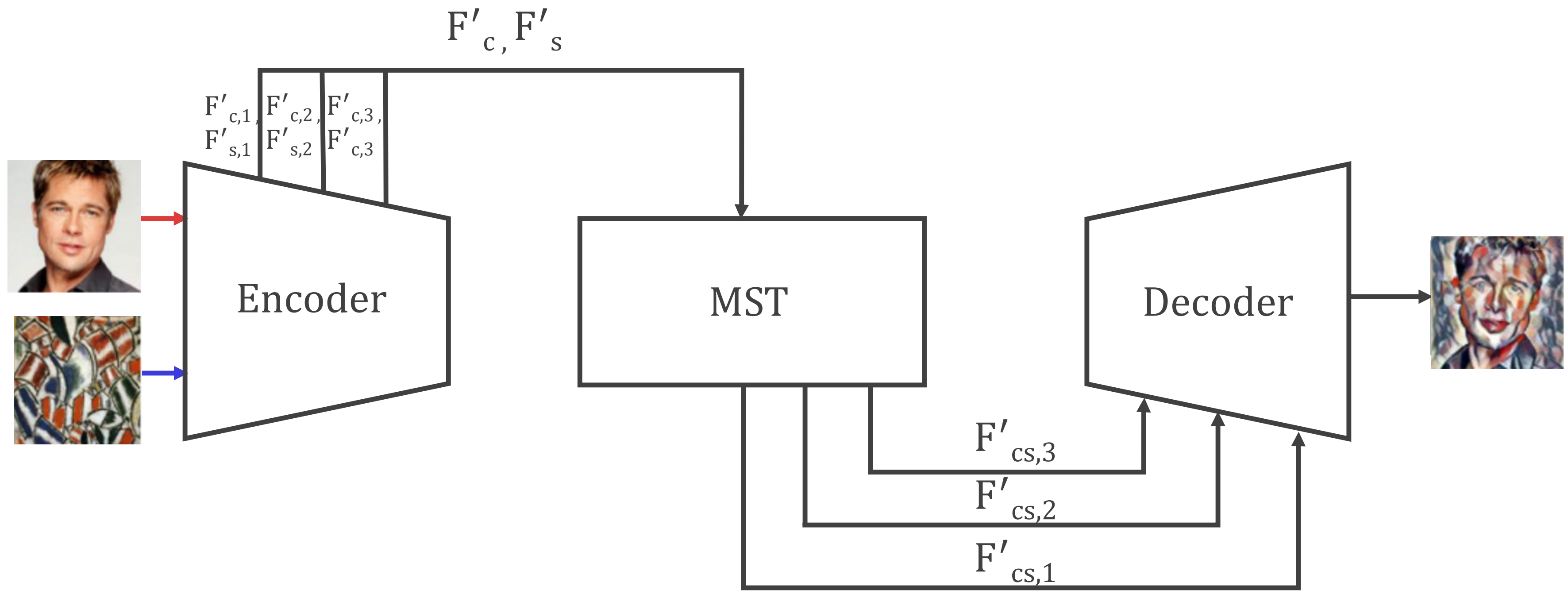
Minseong Kim, Hyun-Chul Choi, ICLR, 2019



(a) Content (b) Style (c) Gatys et al. (d) Huang et al. (e) Li et al. (f) Ours-intra (e) Ours-inter

05 Total Style Transfer With A Single Feed-forward Network

Minseong Kim, Hyun-Chul Choi, ICLR, 2019



MST(Multi-scaled style transformer) : 내부 SST와 skip-connected decoder를 사용하여 multi-scaled style을 transfer 함

05

Total Style Transfer With A Single Feed-forward Network

Minseong Kim, Hyun-Chul Choi, ICLR, 2019

$$L_{content} = \ Gatys\ et\ al. (2016)$$
$$L_{style_{intra}},\ L_{style_{inter}}$$

$\mathrm{L_{content}}$: Content loss

$\mathrm{L_{style_{intra}}}$: Correlations between channels in each scale

$\mathrm{L_{style_{inter}}}$: Correlations between scales

05 Total Style Transfer With A Single Feed-forward Network

Minseong Kim, Hyun-Chul Choi, ICLR, 2019

$$L_{content} = \ Gatys\ et\ al.(2016)$$
$$L_{style_{intra}},\ L_{style_{inter}}$$

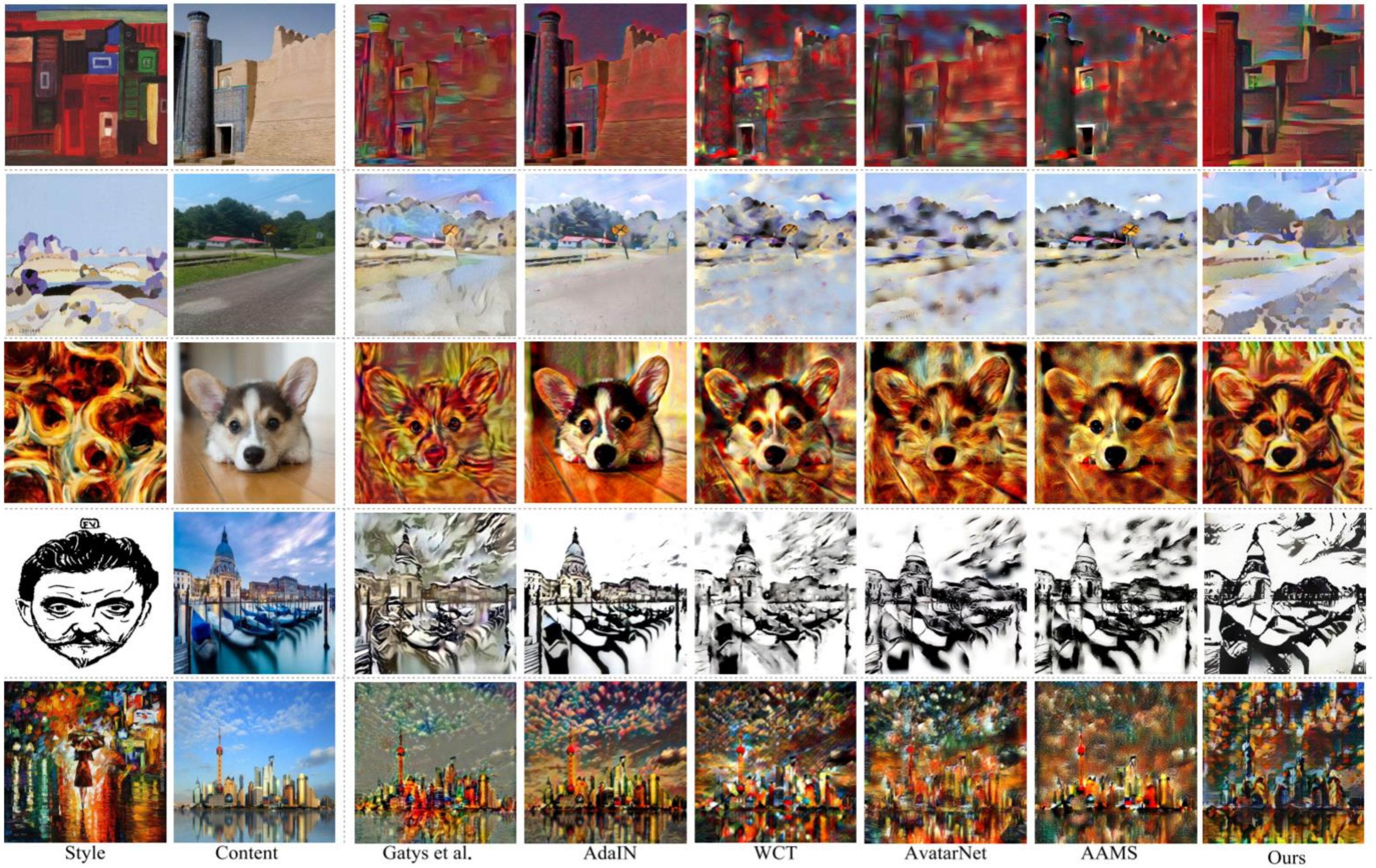
$$L_{style_{intra}} = \sum_i ||\mu_{s,i} - \mu_{o,i}|| + \sum_i ||cov(\bar{F}_{s,i}) - cov(\bar{F}_{o,i})||, \quad (5)$$

$$L_{style_{inter}} = ||\mu'_s - \mu'_o|| + ||cov(\bar{F'}_s) - cov(\bar{F'}_o)||, \quad (6)$$

$\bar{F}s, i$: i th zero − centered feature of style image (o : output)
$\bar{F}'_s$: concatenated feature of style image
cov : covariance matrix

ETNet: Error Transition Network for Arbitrary Style Transfer

Chunjin Song, Zhijie Wu, Yang Zhou, Minglun Gong, Hui Huang, NIPS, 2019



06 ETNet: Error Transition Network for Arbitrary Style Transfer

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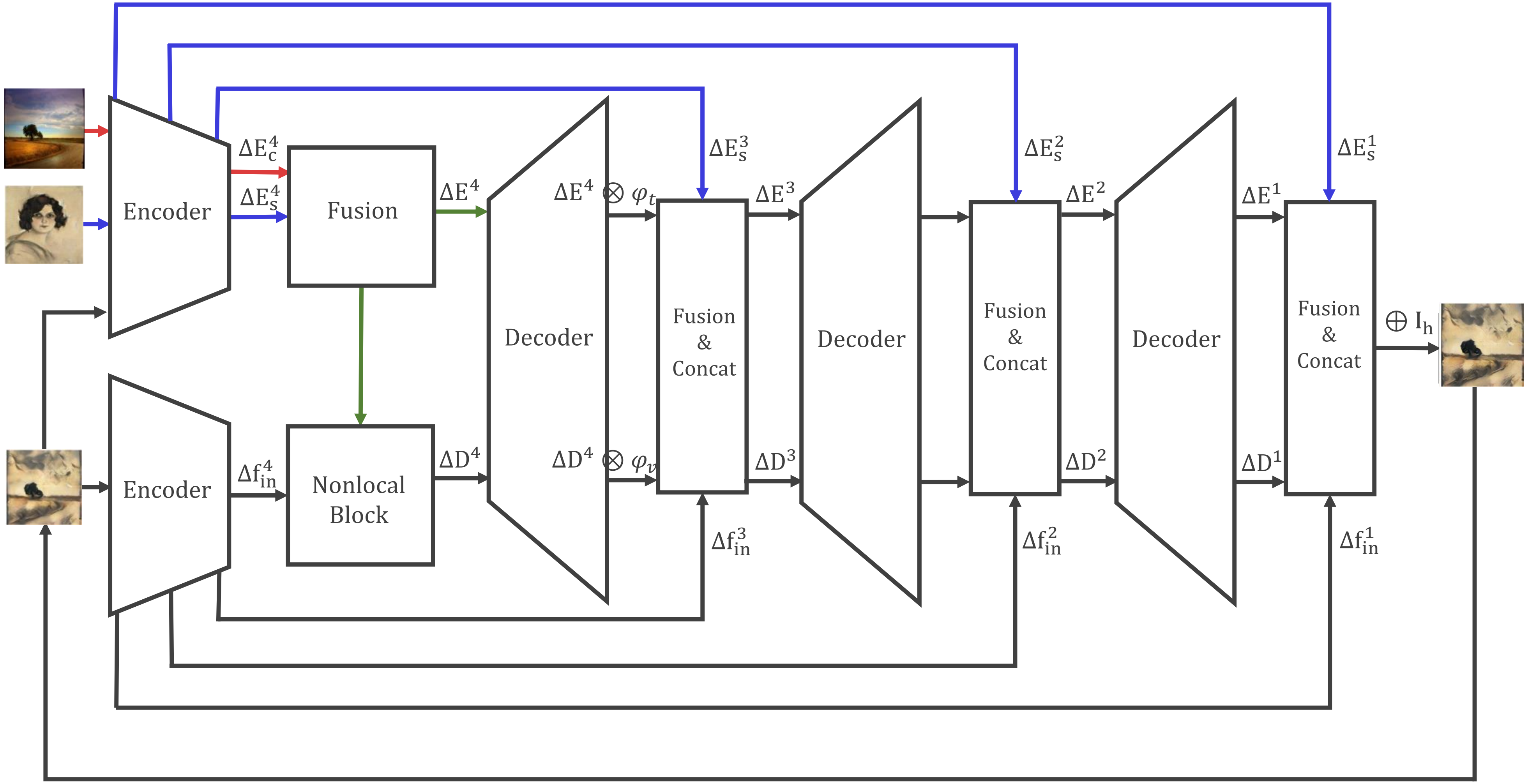


1st Fusion : 두 E를 합침
Nonlocal Block : globel residual feature를 추출
2nd Fusion and Concat : 더 lower한 level의 information 을 추출하기 위한 모듈

06

ETNet: Error Transition Network for Arbitrary Style Transfer

Chunjin Song, Zhijie Wu, Yang Zhou, Minglun Gong, Hui Huang, NIPS, 2019

$$\boxed{L_{total}^{k} = \lambda_{pc}^{k} L_{pc}^{k} + \lambda_{ps}^{k} L_{ps}^{k} + \lambda_{tv}^{k} L_{TV}}$$

* Total Loss at k-th level of a pyramid (k =1,2,3)

L_{pc}^{k} : content loss

L_{ps}^{k} : style loss

L_{TV} : Total variation loss (means adding to acheieve the piece $-$ wise smoothness)

06 ETNet: Error Transition Network for Arbitrary Style Transfer

Chunjin Song, Zhijie Wu, Yang Zhou, Minglun Gong, Hui Huang, NIPS, 2019

$$L^k_{total} = \lambda^k_{pc} L^k_{pc} + \lambda^k_{ps} L^k_{ps} + \lambda^k_{tv} L_{TV}$$

$$L^k_{pc} = \|\Phi_{vgg}(I^k_c) - \Phi_{vgg}(I^k_{cs})\|_2 + \sum_{j=k+1}^{K} \|\Phi_{vgg}(I^j_c) - \Phi_{vgg}(\tilde{I}^j_{cs})\|_2, \tag{7}$$

$$L^k_{ps} = \sum_{i=1}^{L} \|G^i(I^k_s) - G^i(I^k_{cs})\|_2 + \sum_{j=k+1}^{K} \|G^L(I^j_s) - G^L(\tilde{I}^j_{cs})\|_2, \tag{8}$$

Φ_{vgg} : VGG Encoder

G^i : Gram matrix for features extracted at layer i in the encoder network

I^k_c : input image

$\tilde{I}^j_{cs}$: (j-k) repeated applications of downsampling operation $\mathrm{d}(\cdot)$ on I^k_{cs}

(e.g. k=1. $\tilde{I}^3_{cs} = \mathrm{d}(\mathrm{d}(I^1_{cs}))$ (To capture large patterns)

set $\mathrm{L} = 4$

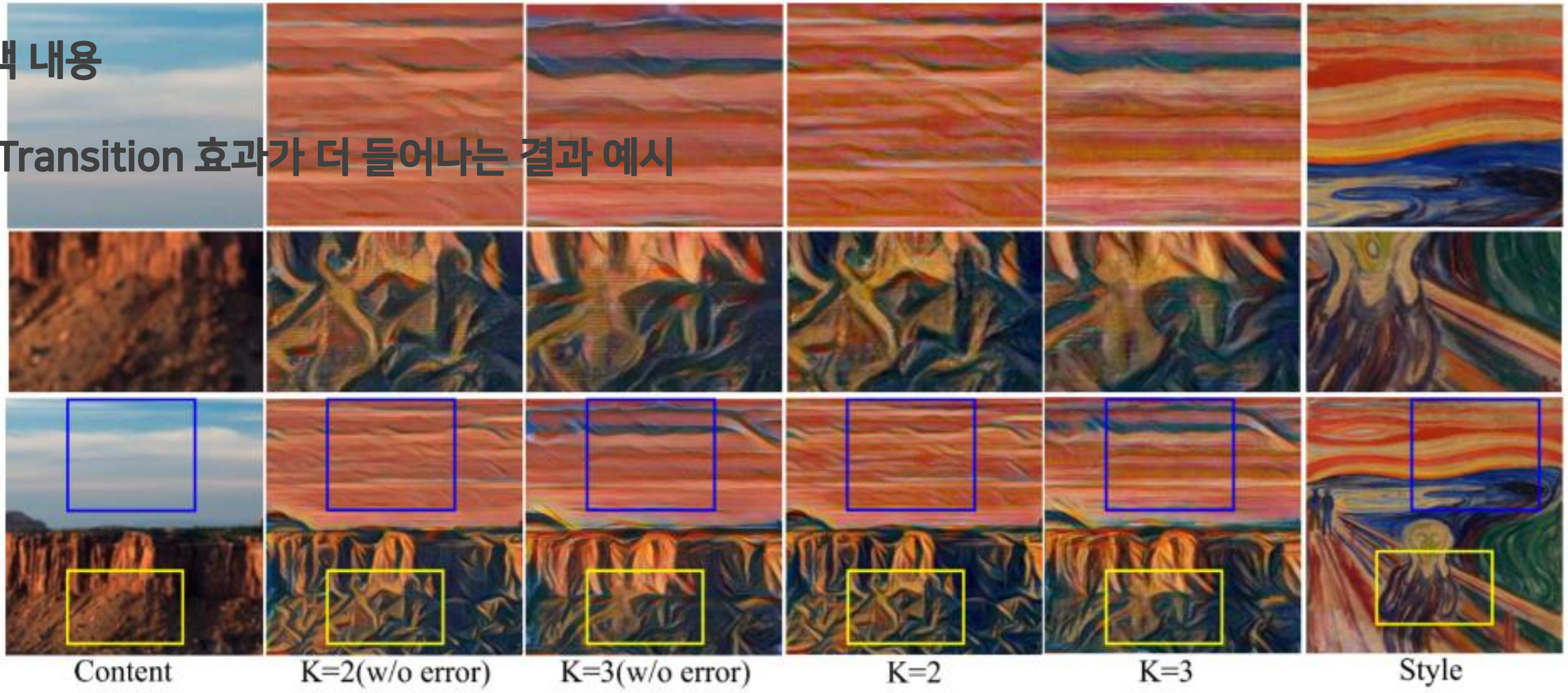
06

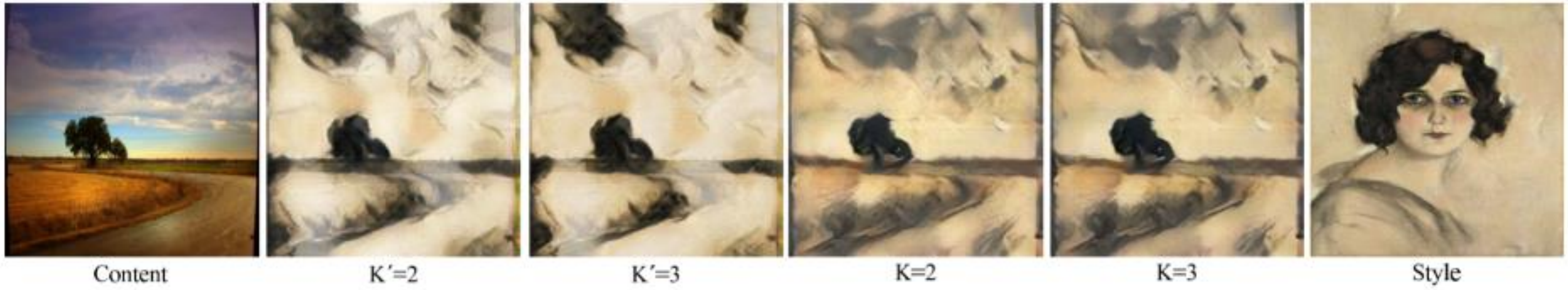
ETNet: Error Transition Network for Arbitrary Style Transfer

Chunjin Song, Zhijie Wu, Yang Zhou, Minglun Gong, Hui Huang, NIPS, 2019

2차 피드백 내용

Q. Error Transition 효과가 더 들어나는 결과 예시

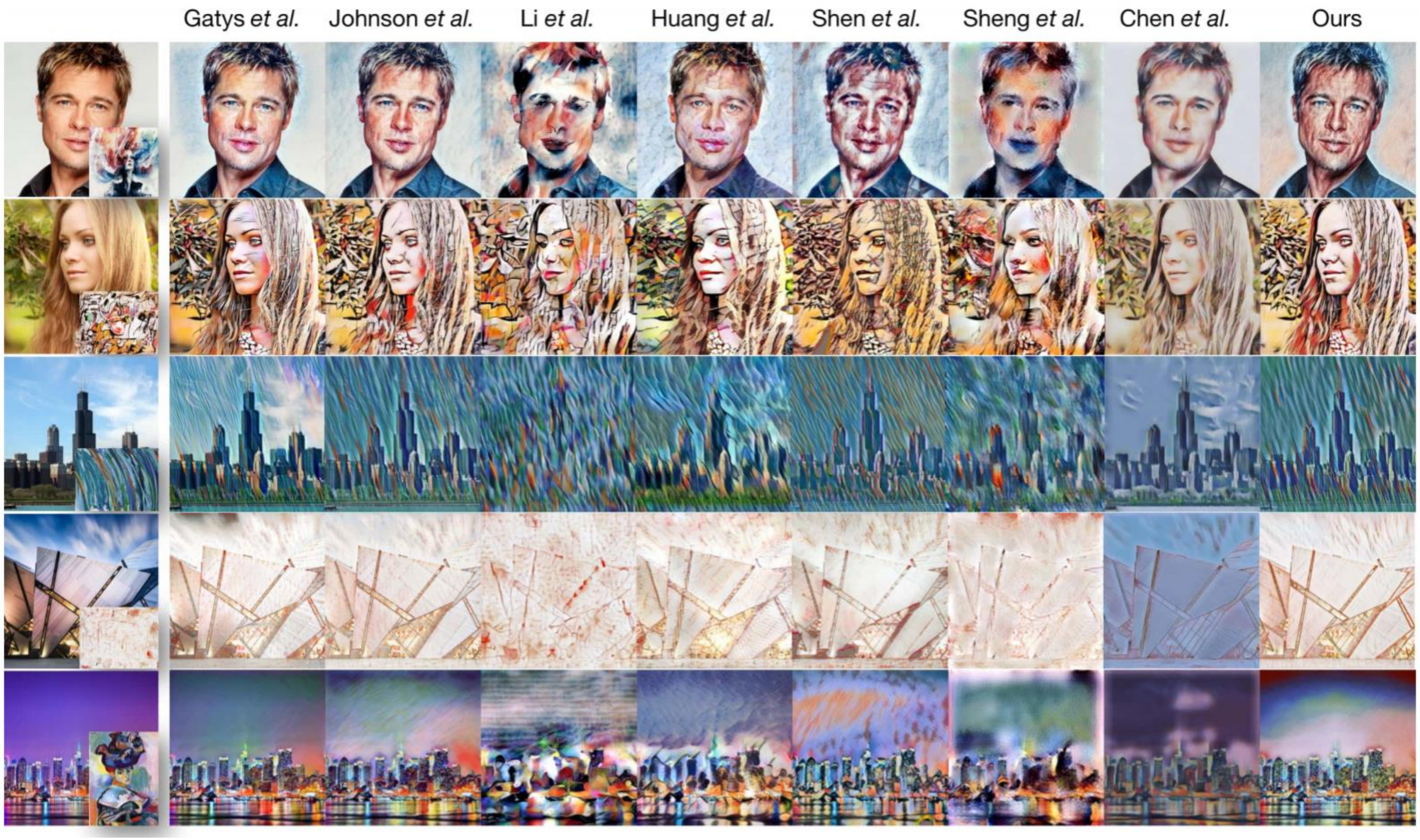




07

MetaStyle
: Three-Way Trade-off among Speed, Flexibility, and Quality in Neural Style Transfer

Chi Zhang, Yixin Zhu, Song-Chun Zhu, AAAI, 2019



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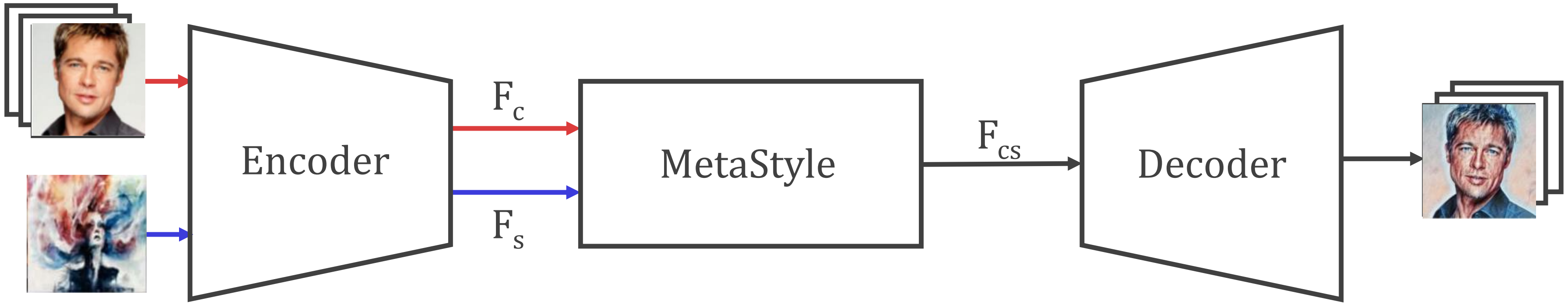


MetaStyle : 각각의 이미지에 대한 inner loss와 outer loss를 계산하여 스타일에 중립적인 표현을 배우고 새로운 스타일을 적용을 위한 일정 업데이트를 거침

07

MetaStyle
: Three-Way Trade-off among Speed, Flexibility, and Quality in Neural Style Transfer

Chi Zhang, Yixin Zhu, Song-Chun Zhu, AAAI, 2019

$$E_{c,s}[\, l(I_c, I_s, M\big(I_c; w_{s,T}\big)]$$
$$E_c[\, l(I_c, I_s, M\big(I_c; w_{s,t-1}\big)]$$

$$\begin{aligned} \underset{\theta}{\text{minimize}} \quad & \mathbb{E}_{c,s}[\ell(I_c, I_s, M(I_c; w_{s,T}))] \\ \text{subject to} \quad & w_{s,0} = \theta \\ & w_{s,t} = w_{s,t-1} - \delta \nabla \mathbb{E}_c[\ell(I_c, I_s, M(I_c; w_{s,t-1}))], \end{aligned} \tag{7}$$

$E_{c,s}$: outer loss, respect style and content image in the validation set

L_θ , E_c: inner loss, respect content image in the training set

→ single style 에 특화 & 일반적인 initialization 유지

M : model

δ : learning rate of inner class

07 MetaStyle
: Three-Way Trade-off among Speed, Flexibility, and Quality in Neural Style Transfer

Chi Zhang, Yixin Zhu, Song-Chun Zhu, AAAI, 2019

2차 피드백 내용

Q. Speed And Flexibility

Method	Param	256 (s)	512 (s)	# Styles
Gatys *et al.*	N/A	7.7428	27.0517	∞
Johnson *et al.*	**1.68M**	**0.0044**	**0.0146**	1
Li *et al.*	34.23M	0.6887	1.2335	∞
Huang *et al.*	7.01M	0.0165	0.0320	∞
Shen *et al.*	219.32M	**0.0045**	**0.0147**	∞
Sheng *et al.*	147.22M	0.5089	0.6088	∞
Chen *et al.*	**1.48M**	0.2679	1.0890	∞
Ours	**1.68M**	**0.0047**	**0.0145**	$\infty^{\star}$

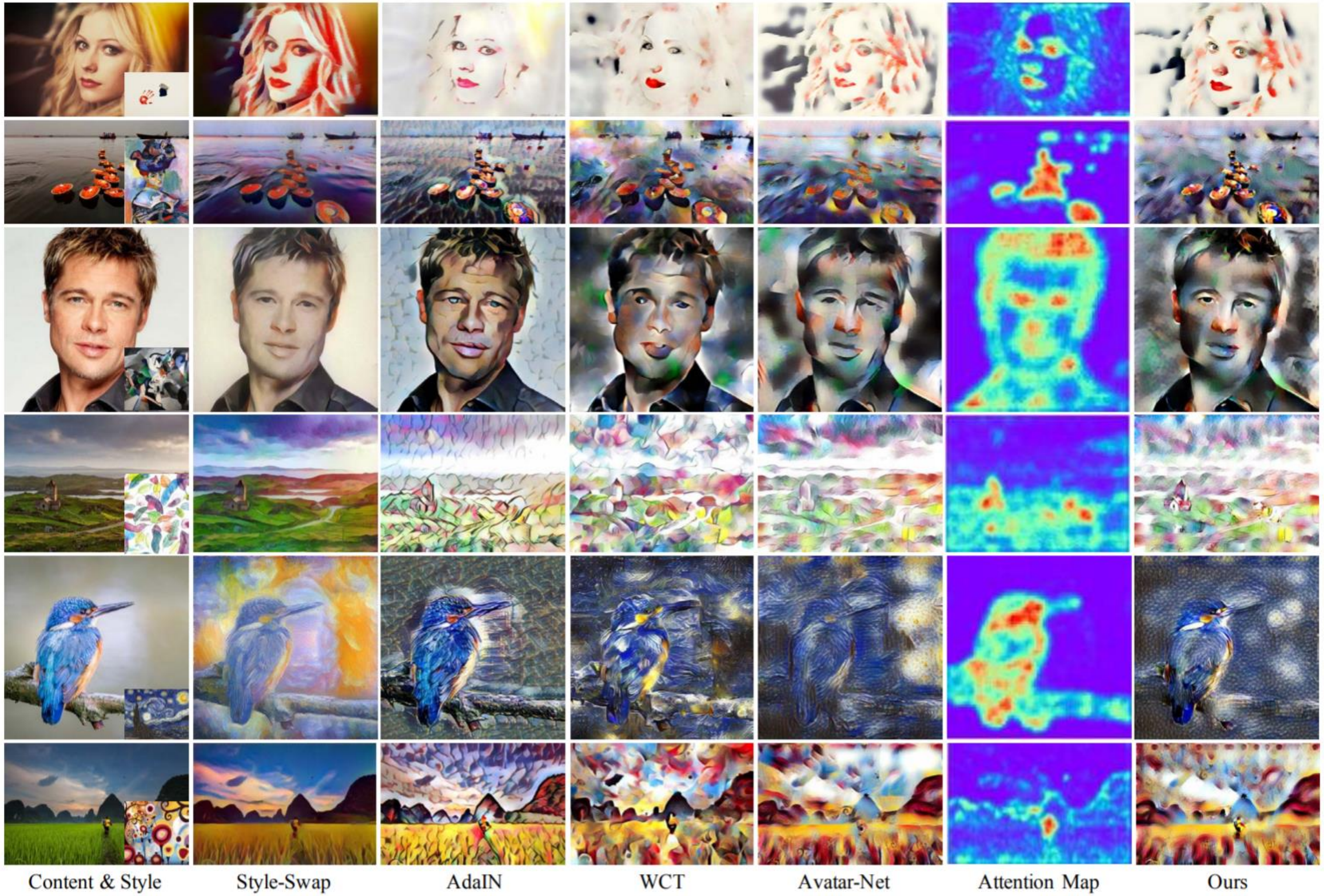
- 256/ 512 : 256 * 256 input, 512 * 512 input
  - # Style : 모델이 처리 할 수 있는 스타일의 수

➔ MetaStyle은 적은 업데이트 단계 이후 특정 스타일을 적용 가능 함

08

Attention-Aware Multi-Stroke Style Transfer

Yuan Yao, Jianqiang Ren, Xuansong Xie, Weidong Liu, Yong-Jin Liu, Jun Wang, CVPR, 2019



08 Attention-Aware Multi-Stroke Style Transfer

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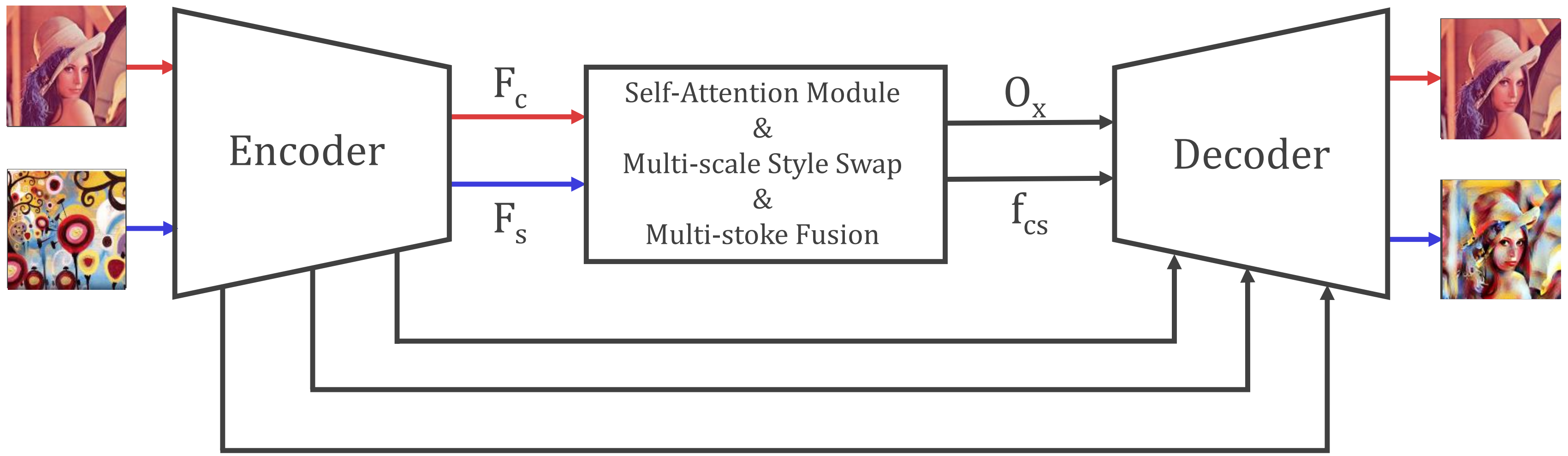


Self-Attention Module : Content의 두드러진 특징을 학습하고 모든 이미지의 content에 대한 activation feature map A_c를 생성하고 f_c와 연산되어 O_x를 출력
Multi-scale Style Swap : Style의 activation feature scale을 변경하며 패치 크기를 수정, content feature와 K style feature에 대한 style swap을 수행
K : user가 부여한 Clustering 번호로 Patch 별 가장 가까운 style feature로 content featurㄷ를 교체(Swap)
Multi-stroke fusion : arbitrary stroke를 통합하기 위해 attention map $\hat{A}_c^k$를 여러 cluster로 분할하여 유연하게 $\hat{f}_{cs}^k$와 융합

08 Attention-Aware Multi-Stroke Style Transfer

Yuan Yao, Jianqiang Ren, Xuansong Xie, Weidong Liu, Yong-Jin Liu, Jun Wang, CVPR, 2019

$$\boxed{L = \lambda_{con} L_{con} + \lambda_{att} L_{att} + \lambda_{tv} L_{tv}}$$

* Total Loss at k-th level of a pyramid (k =1,2,3)

L_{con}: Semantic content loss(perceptual loss + pixel loss)
L_{att} : Sparse loss of self attention map A_x (for attention to smaller region)
L_{tv} : Total variation regularization loss (for spatial smoothness)

08 Attention-Aware Multi-Stroke Style Transfer

Yuan Yao, Jianqiang Ren, Xuansong Xie, Weidong Liu, Yong-Jin Liu, Jun Wang, CVPR, 2019

$$L = \lambda_{con} L_{con} + \lambda_{att} L_{att} + \lambda_{tv} L_{tv}$$

$$\mathcal{L}_{con} = \sum_{l \in l_c} ||\phi_l(\hat{x}) - \phi_l(x)||_2^2 + \lambda_p ||\hat{x} - x||_2^2 , \quad (5)$$

$$\mathcal{L}_{att} = ||A_x||_1 . \quad (6)$$

$\hat{x}$: reconstruction of the input image

$\varphi_l(x)$: activations of the lth layer of the pre-trained VGG-19 network when processing image x

A_x : self-attention feature map (for awareness to small regions instead of the whole image)

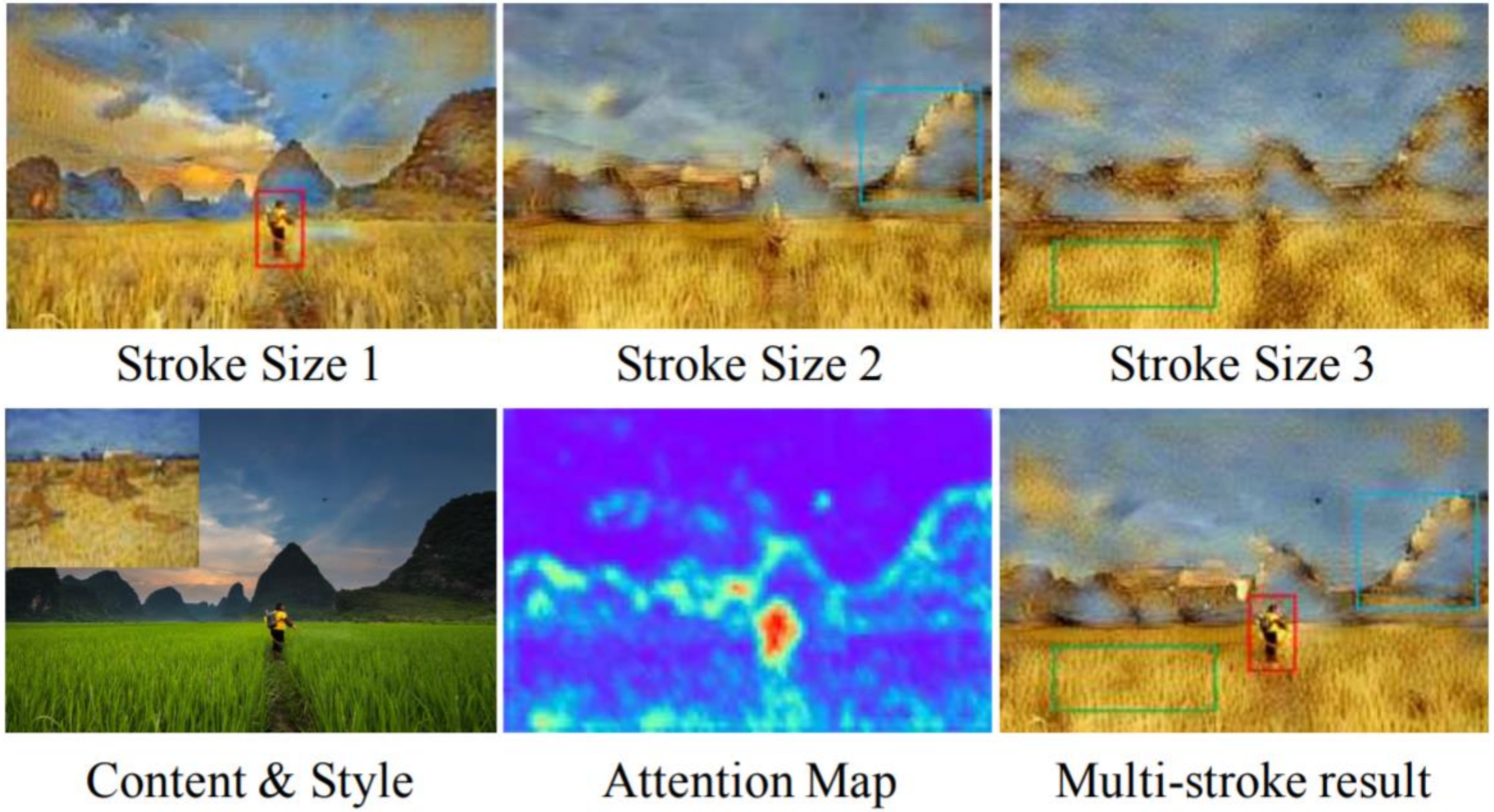
L_{tv} : J. Johnson, A. Alahi, and L. Fei-Fei. Perceptual losses for real-time style transfer and super-resolution. In ECCV, 2016

08 Attention-Aware Multi-Stroke Style Transfer

Yuan Yao, Jianqiang Ren, Xuansong Xie, Weidong Liu, Yong-Jin Liu, Jun Wang, CVPR, 2019

2차 피드백 내용

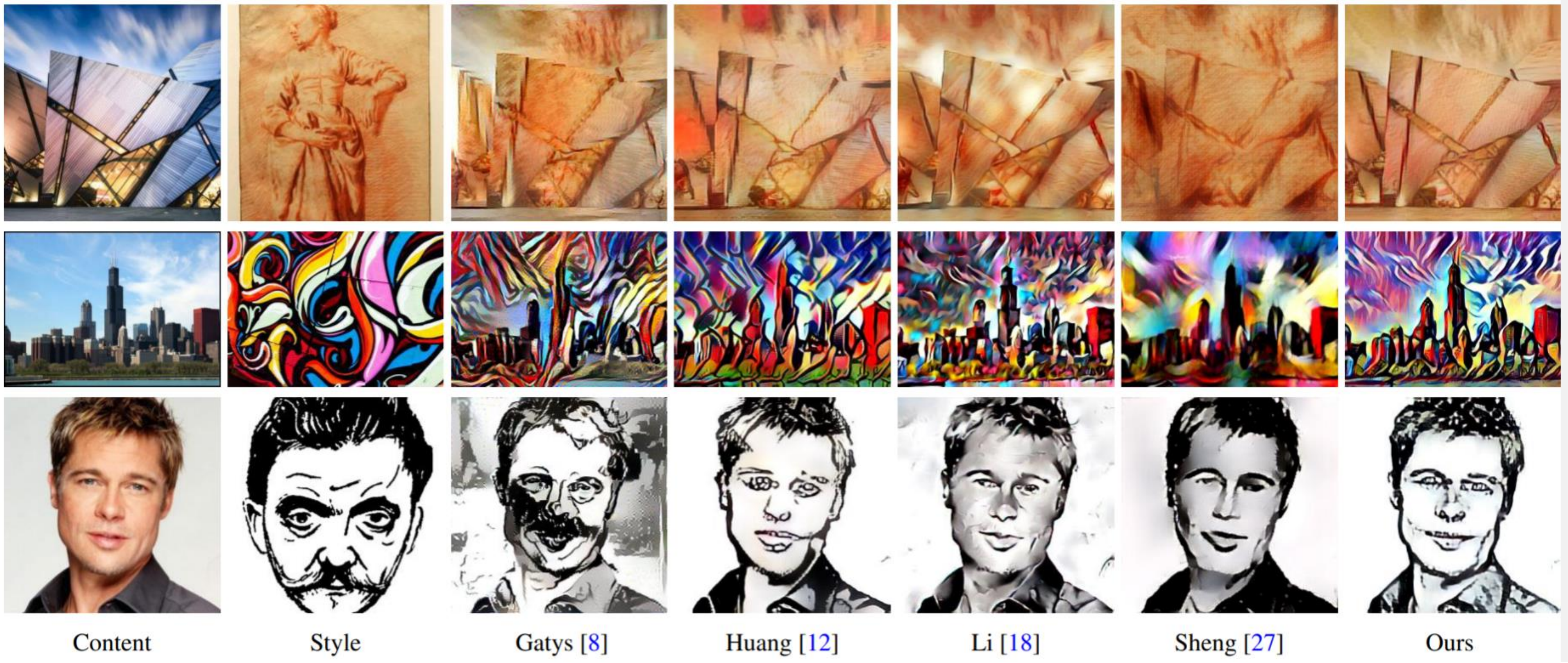
Q. Stroke차이
A.



09

Learning Linear Transformations for Fast Image and Video Style Transfer

Xueting Li, Sifei Liu, Jan Kautz, Ming-Hsuan Yang, CVPR, 2019



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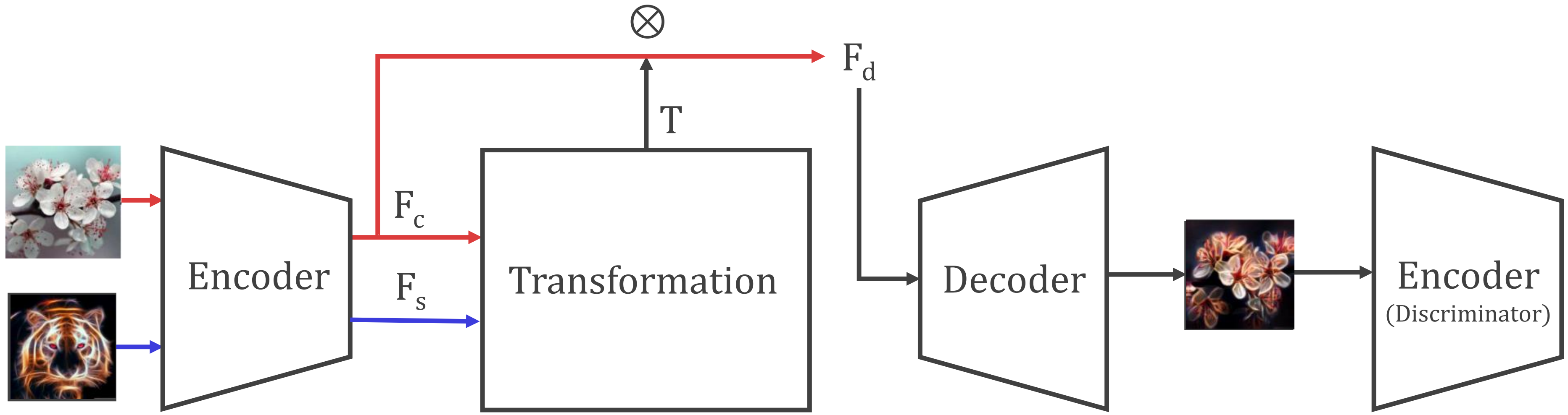


Transformation : 두 개의 독립적인 CNN을 사용하여 F_c , F_s에 대한 공분산 행렬을 이용하여 두 feature를 multiplication 함
* T는 출력 F_d에서 style이 content 이미지의 global & local 한 부분 모두 고르게 적용되길 바람

Learning Linear Transformations for Fast Image and Video Style Transfer

Xueting Li, Sifei Liu, Jan Kautz, Ming-Hsuan Yang, CVPR, 2019

$$F_d^* = \arg\min_{F_d} \frac{1}{NC} \|\bar{F_d}\bar{F_d}^\top - \bar{\phi_s}\bar{\phi_s}^\top\|_F^2$$
$$s.t. \bar{F_d} = T\bar{F_c}.$$

$$T = \left(V_s D_s^{\frac{1}{2}} V_s^\top\right) U \left(V_c D_c^{-\frac{1}{2}} V_c^\top\right), \qquad (3)$$

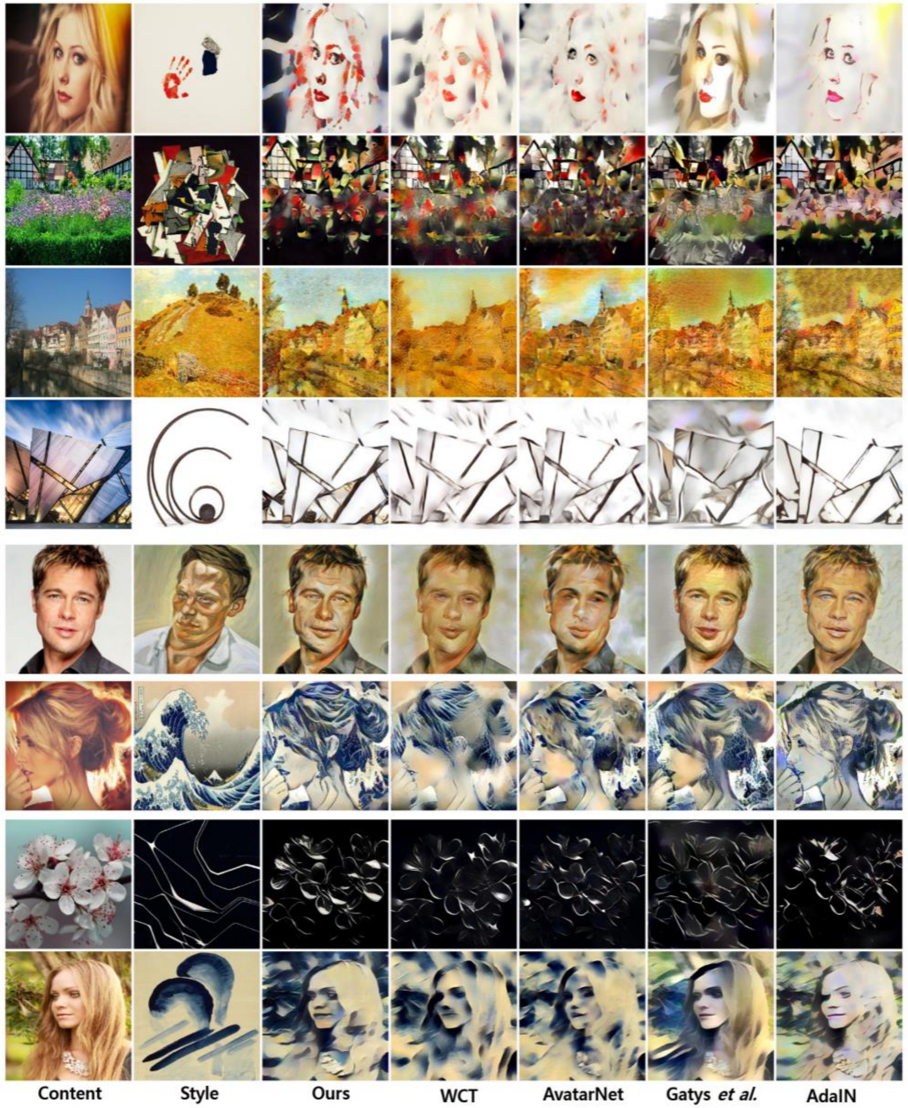
* Difference of centered covariance between F_d and φ_s

U : c-channel orthogonal group
VDV : singular value decomposition(SVD)
F_d : transformed feature vector
$\bar{F}_c$: vectorized feature map F_c with zero mean

L_c : J. Johnson, A. Alahi, and L. Fei-Fei. Perceptual losses for real-time style transfer and super-resolution. In ECCV, 2016,
X. Huang and S. Belongie. Arbitrary style transfer in realtime with adaptive instance normalization. In ICCV, 2017.

10 Arbitrary Style Transfer With Style-Attentional Networks

Dae Young Park, Kwang Hee Lee, CVPR, 2019



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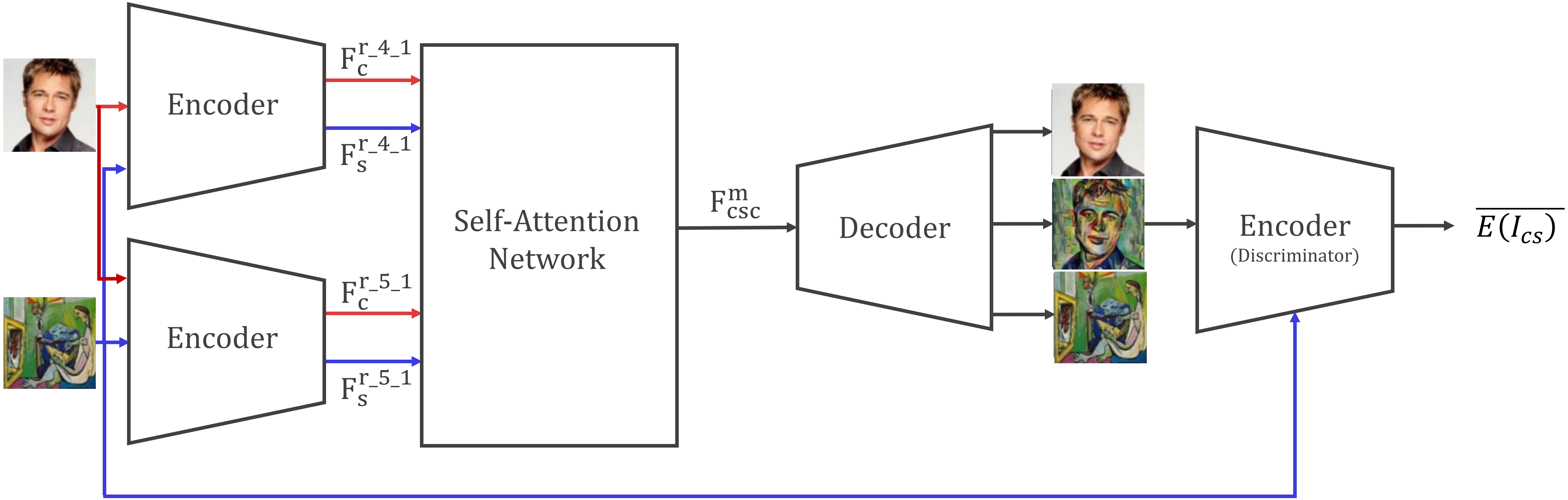
Dae Young Park, Kwang Hee Lee, CVPR, 2019



Self-Attention Network : global style pattern 과 local style pattern 을 적절히 융합하기 위해 서로 다른 레이어에서 나온 feature map 을 결합

10 Arbitrary Style Transfer With Style-Attentional Networks

Dae Young Park, Kwang Hee Lee, CVPR, 2019

$$\boxed{L_{total} = \lambda_c L_c + \lambda_s L_s + L_{identity}}$$

L_c : content loss (Euclidean distance between the mean-variance channel-wise normalized target feature)

L_s : style loss

$L_{identity}$: identity loss

Arbitrary Style Transfer With Style-Attentional Networks

Dae Young Park, Kwang Hee Lee, CVPR, 2019

$$L_{total} = \lambda_c L_c + \lambda_s L_s + L_{identity}$$

$$\mathcal{L}_c = ||\overline{E(I_{cs})^{\text{r\_4\_1}}} - \overline{F_c^{\text{r\_4\_1}}}||_2 + ||\overline{E(I_{cs})^{\text{r\_5\_1}}} - \overline{F_c^{\text{r\_5\_1}}}||_2. \quad (7)$$

$\overline{E(I_{cs})^{r\_4\_1}}, \overline{E(I_{cs})^{r\_5\_1}}$

: mean-variance channel-wise normalized features of the output image VGG features

$$\mathcal{L}_s = \sum_{i=1}^{L} ||\mu(\phi_i(I_{cs})) - \mu(\phi_i(I_s))||_2 + ||\sigma(\phi_i(I_{cs})) - \sigma(\phi_i(I_s))||_2, \quad (8)$$

φ : feature map of the layer in the encoder used to compute the style loss

$$\mathcal{L}_{identity} = \lambda_{identity1}(||(I_{cc} - I_c)||_2 + ||(I_{ss} - I_s)||_2) + \lambda_{identity2} \sum_{i=1}^{L} (||\phi_i(I_{cc}) - \phi_i(I_c)||_2 + ||\phi_i(I_{ss}) - \phi_i(I_s)||_2), \quad (9)$$

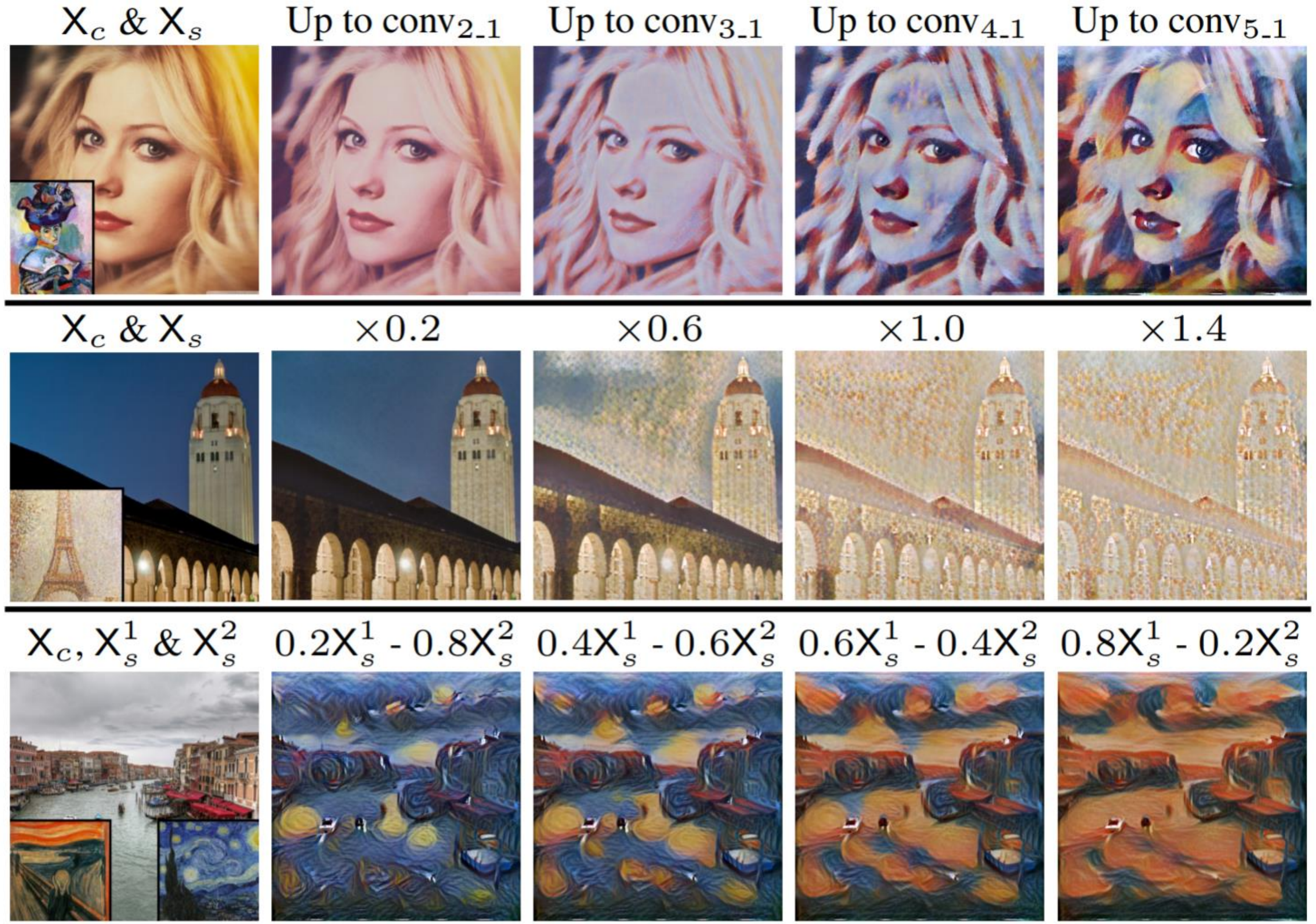
I_{cc} , I_{ss} : output image synthesized from two same content(or style) image

φ_i : layer in the encoder

11

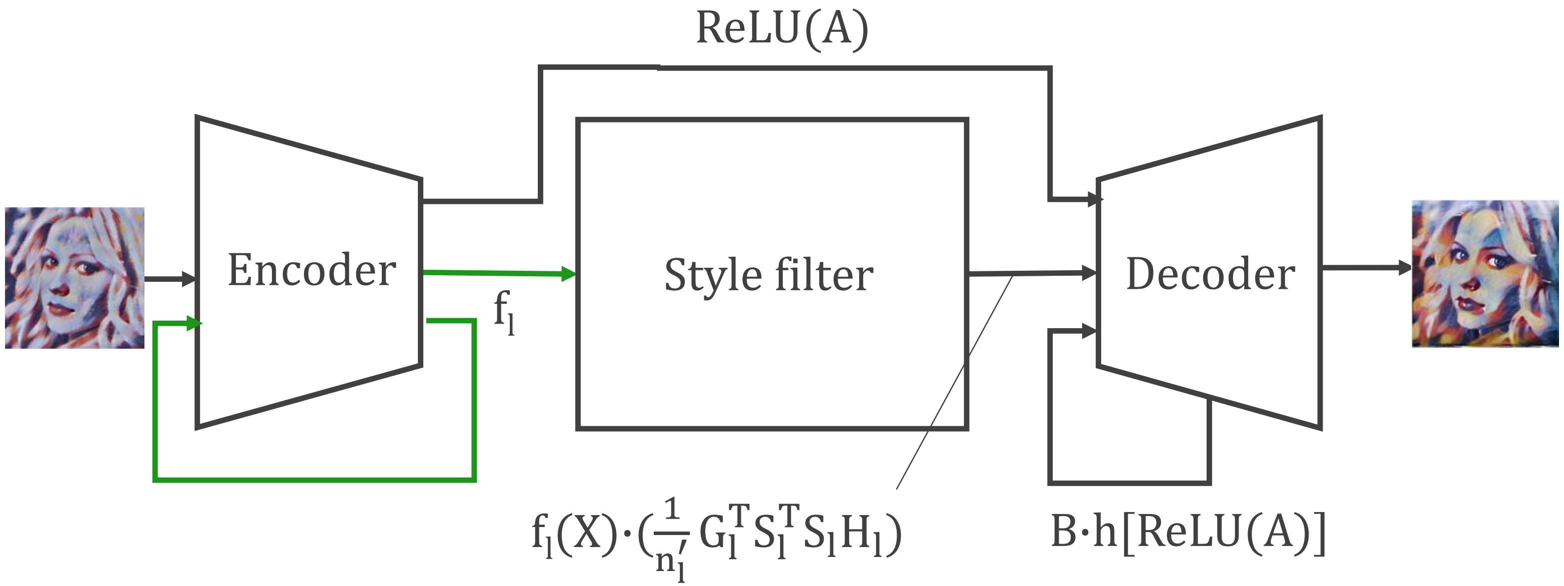
A Flexible Convolutional Solver for Fast Style Transfers

Gilles Puy, Patrick Perez, CVPR, 2019



A Flexible Convolutional Solver for Fast Style Transfers

Gilles Puy, Patrick Perez, CVPR, 2019



$$f_\ell(X)\cdot\left(\frac{1}{n'_\ell}G_\ell^T S_\ell^T S_\ell H_\ell\right) \rightarrow \frac{1}{n'_\ell} f_\ell(X)\cdot\left[G_\ell^T\left(\sum_i \alpha_i S_\ell^T[X_s^i]S_\ell[X_s^i]\right)H_\ell\right]. \quad (12)$$

Style filter : style control을 위한 필터로 각 scale에서 특성 f_l을 독립적으로 필터링하여 제어 가능함

A Flexible Convolutional Solver for Fast Style Transfers

Gilles Puy, Patrick Perez, CVPR, 2019

$$\boxed{\nabla L_s = \sum_{l \in I_s} \lambda_s^l \nabla L_s^l}$$

$$g(\mathsf{X}, \mathsf{X}_s) = \sum_{\ell \in \mathcal{I}_s} \lambda_s^\ell \, b_\ell \left(\frac{1}{n'_\ell} f_\ell(\mathsf{X}) \times \mathsf{G}_\ell^\intercal \, \mathsf{S}_\ell^\intercal \mathsf{S}_\ell \, \mathsf{H}_\ell \right). \quad (10)$$

$$\sum_{\ell \in \mathcal{I}_s} \frac{\lambda_s^\ell}{c_\ell^2} \sum_i \left\| \frac{1}{n_\ell} (\mathsf{M}_\ell^i \mathsf{F}_\ell)^\intercal (\mathsf{M}_\ell^i \mathsf{F}_\ell) - \frac{1}{n'_\ell} \mathsf{S}_\ell^\intercal [\mathsf{X}_s^i] \mathsf{S}_\ell [\mathsf{X}_s^i] \right\|_{\mathrm{F}}^2 .$$

** top : Archetecture of g_t*

** bottom : Runtime modification of the style loss*

$G_l^T S_l^T S_l H_l$: style filter, governs the style that is applied to the input image (S_l : style feature)

$f_l(X)$: l layer feature

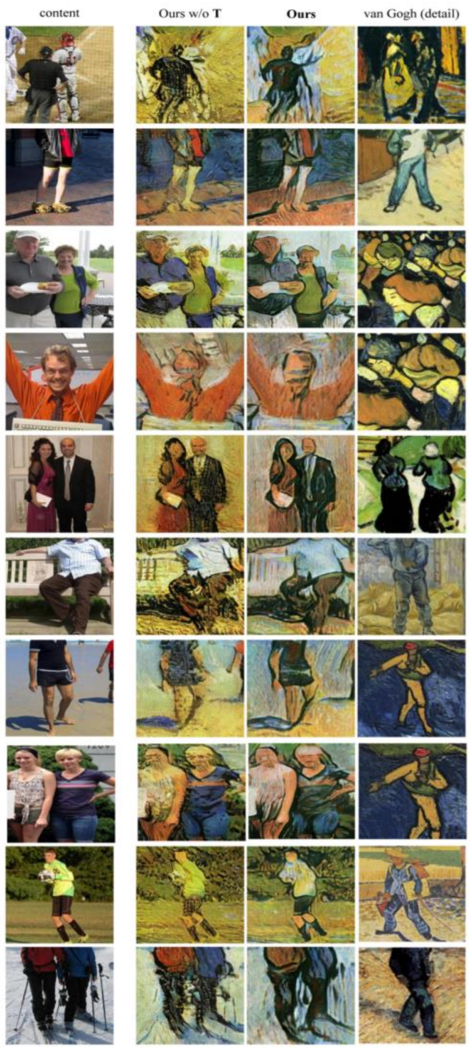
M_l^i : mask at layer l for the ith style and ith region

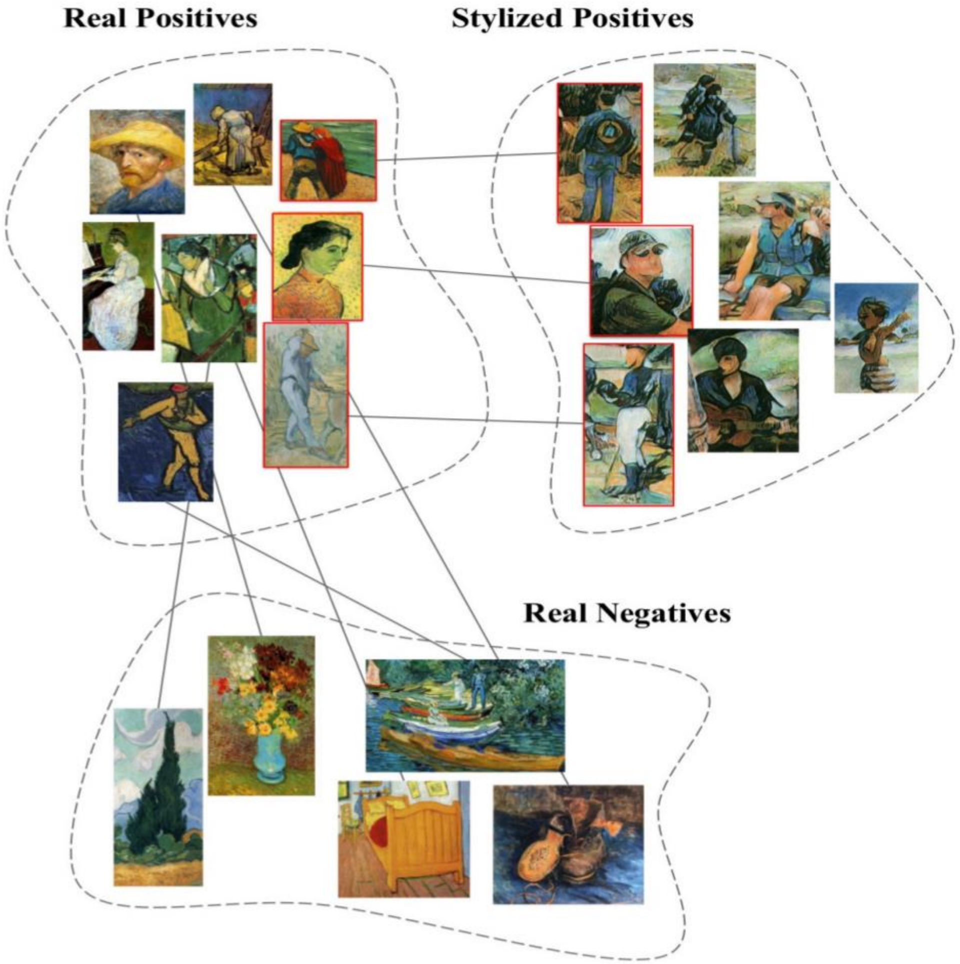
F_l : result feature of $f_l(X)$

X : image

12 A Content Transformation Block for Image Style Transfer

Dmytro Kotovenko, Artsiom Sanakoyeu, Pingchuan Ma, Sabine Lang, Bjorn Ommer, CVPR, 2019





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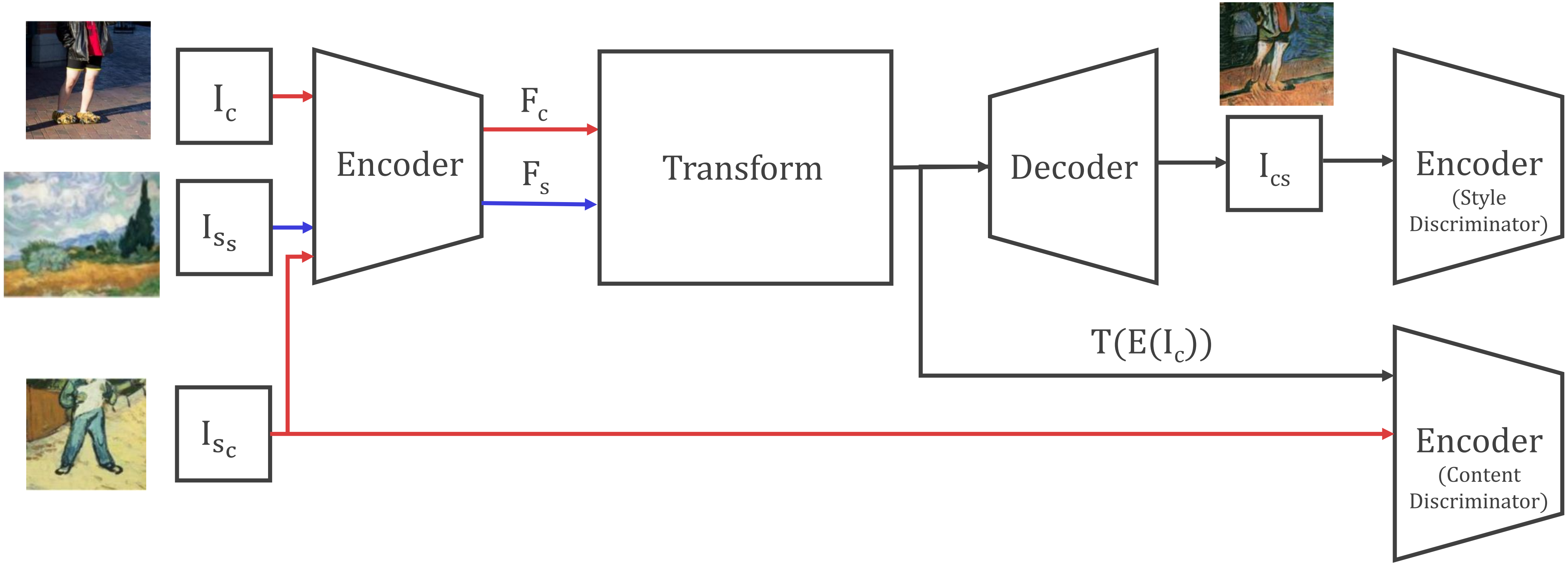

Transform : 스타일의 부분적인 특징에 따라 content 를 변환하도록 학습

A Content Transformation Block for Image Style Transfer

Dmytro Kotovenko, Artsiom Sanakoyeu, Pingchuan Ma, Sabine Lang, Bjorn Ommer, CVPR, 2019

$$\text{Step 1}: \min_{\theta_E,\theta_D} \max_{\theta_{E(D)_S}} \lambda_{L_{pxl}} L_{pxl} + \lambda_{L_{FP}} L_{FP} + \lambda_{L_{adv-style}} L_{adv-style}$$

$$\text{Step 2}: \min_{\theta_T} \max_{\theta_{D_C}} \lambda_{L_{adv-cont}} L_{adv-cont} + \lambda_{L_{adv}} L_{adv-style}$$

$$\mathcal{L}_{adv-style} := \mathop{\mathbb{E}}_{(y,c)\sim\mathbf{Y}}[log(\mathcal{D}_s(y))] + \mathop{\mathbb{E}}_{(x,c,s)\sim\mathbf{X}}[log\left(1-\mathcal{D}_s\left(D(\mathcal{T}(E(x)))|s\right)\right)] \quad (8)$$

$$\mathcal{L}_{adv-cont} := \mathop{\mathbb{E}}_{(y,c)\sim\mathbf{Y}}[log(\mathcal{D}_c(E(y)|c))] + \mathop{\mathbb{E}}_{(x,c,s)\sim\mathbf{X}}[log\left(1-\mathcal{D}_c\left(\mathcal{T}(E(x))|c\right)\right)] \quad (9)$$

$$\mathcal{L}_{FP} := \mathop{\mathbb{E}}_{(x,c,s)\sim\mathbf{X}}[\|E(D(\mathcal{T}(E(x)))) - E(x)\|_2^2]. \quad (10)$$

Y : Style Image

X : Photo Image(Content)

L_{pxl} : Pixel similarity

L_{FP} : Fix Point loss (Residual of encoding space)

$L_{adv\text{-}cont}$: Adversarial loss of content

$L_{adv\text{-}style}$: Adversatial loss of style

c : content class

s : scene class

Thank You