Deep learning in Computer Graphics

Computer Graphics Course, Fall 2023

Presenter: Hanh Le

Examples in Graphics


Sketch simplification


Colorization

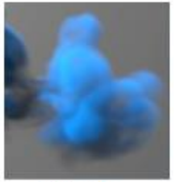

Procedural modelling

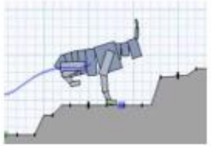

Mesh segmentation

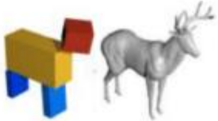

Learning deformations


Real-time rendering

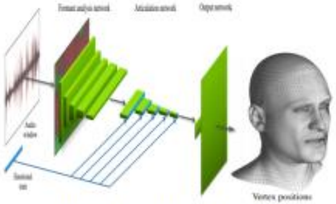

BRDF estimation

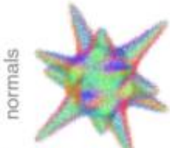

Fluid


Animation


Boxification

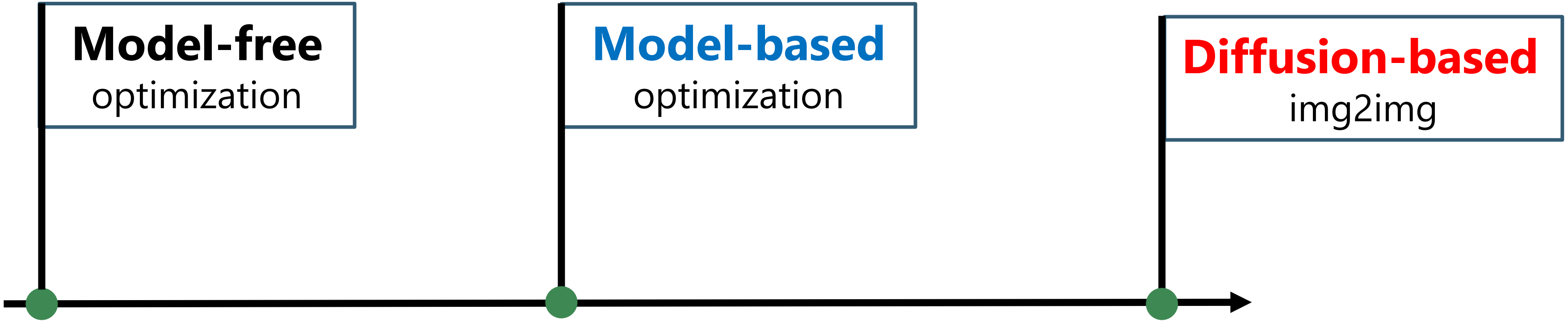

Denoising


Facial animation



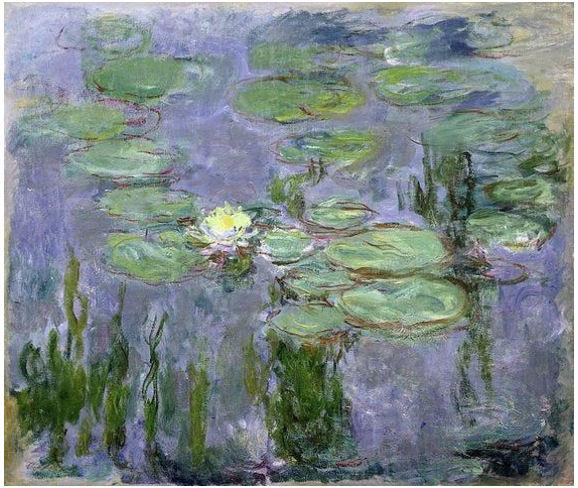
PCD processing

Style Transfer timeline



What is Style Transfer?

What is style transfer?


By Monet Artist

+

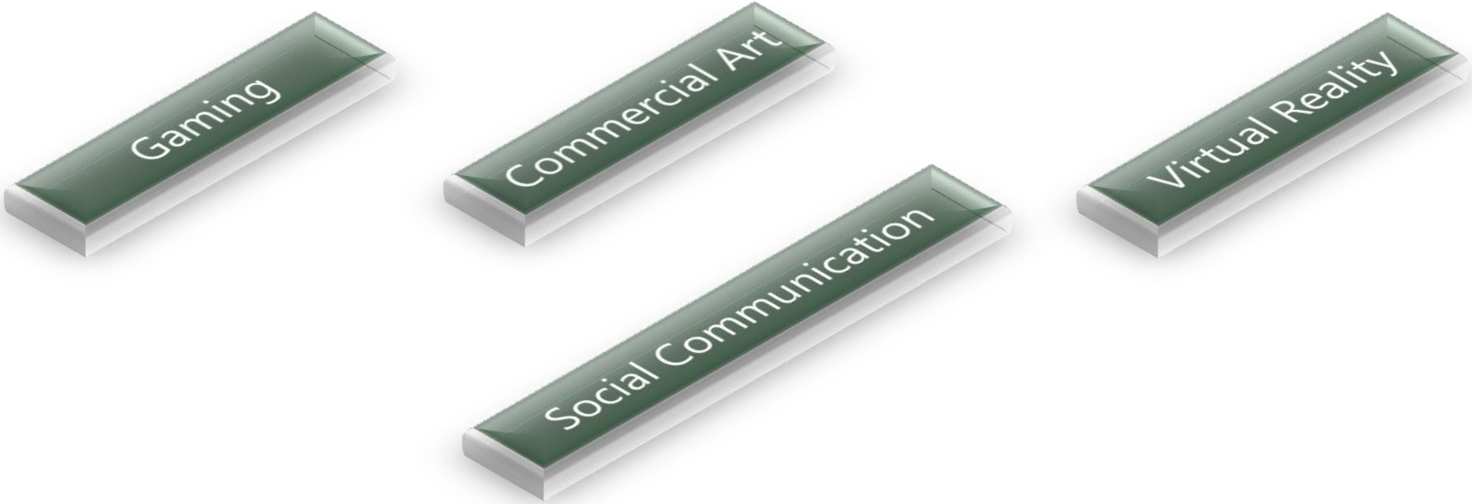

Input content

=


Stylized with Monet’s style

Why Style Transfer?

Applications



Commercial Art

TECH / ARTIFICIAL INTELLIGENCE / CULTURE

Christie's sells its first AI portrait for $432,500, beating estimates of $10,000

Photo: Christie's

/ The image was created using a machine learning algorithm that scanned historical artwork

By JAMES VINCENT
Oct 26, 2018, 1:03 AM GMT+8 | 0 Comments

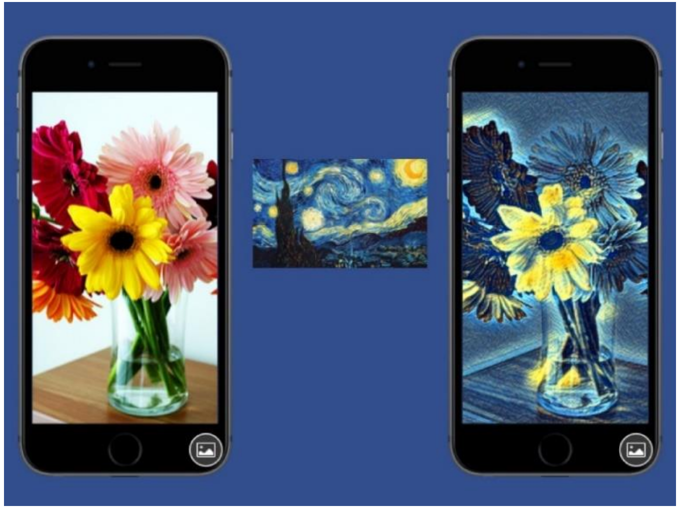
Christie's @ChristiesInc · Follow

#AuctionUpdate The first AI artwork to be sold in a major auction achieves $432,500 after a bidding battle on the phones and via ChristiesLive bit.ly/2PVN2ly

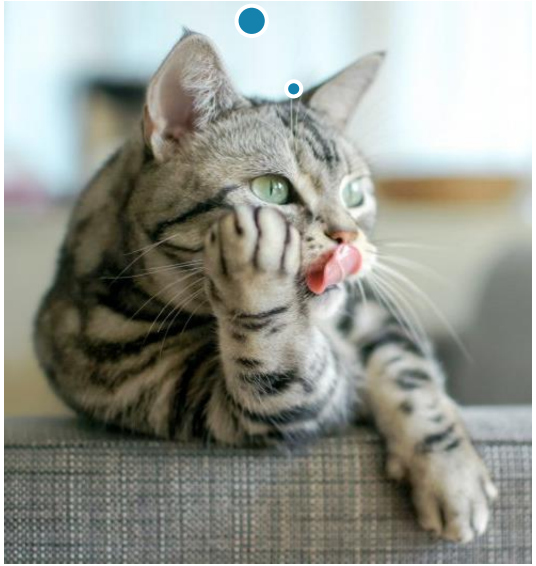
11:22 PM · Oct 25, 2018

1.9K Reply Share

Social communication



How does Style Transfer work?



How Style Transfer methods work?

Style Transfer **with** and **without** neural network.

Model-Optimization-Based Online Neural Methods

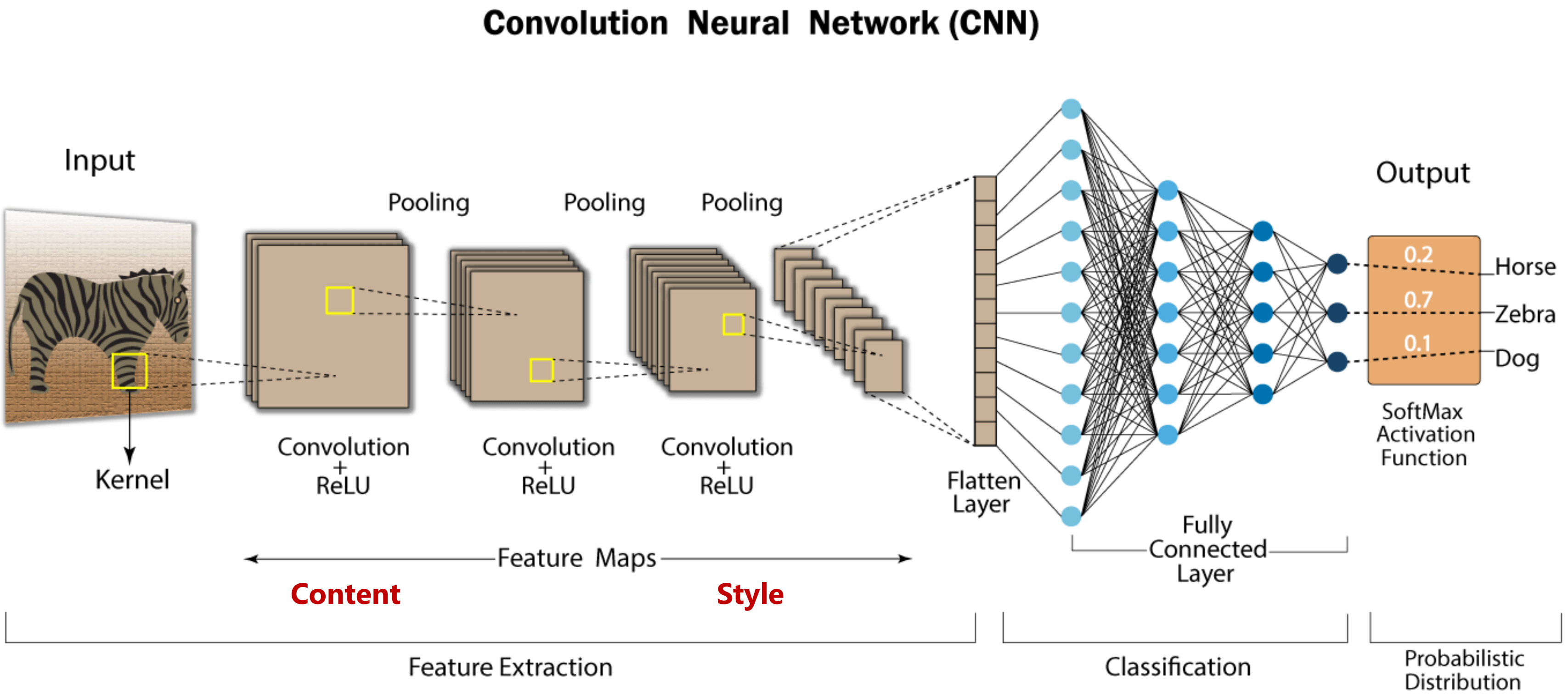
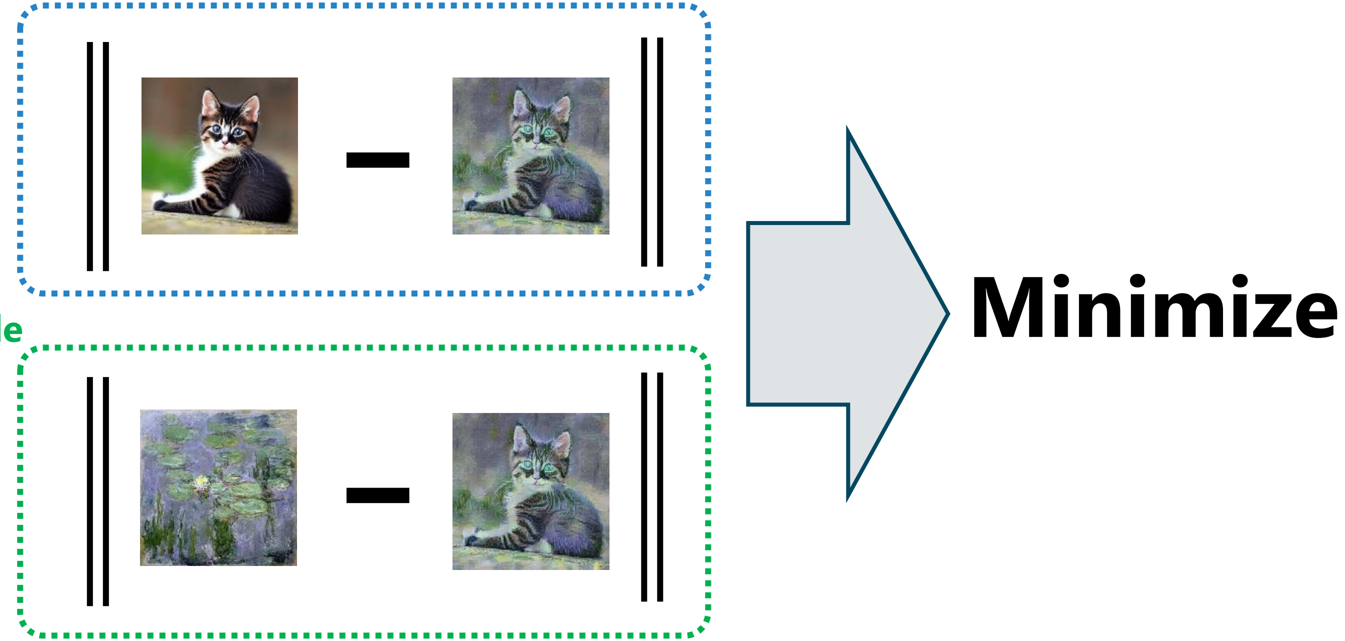


Image source: https://developersbreach.com/convolution-neural-network-deep-learning

Style Transfer without Neural Networks

Similarity of content

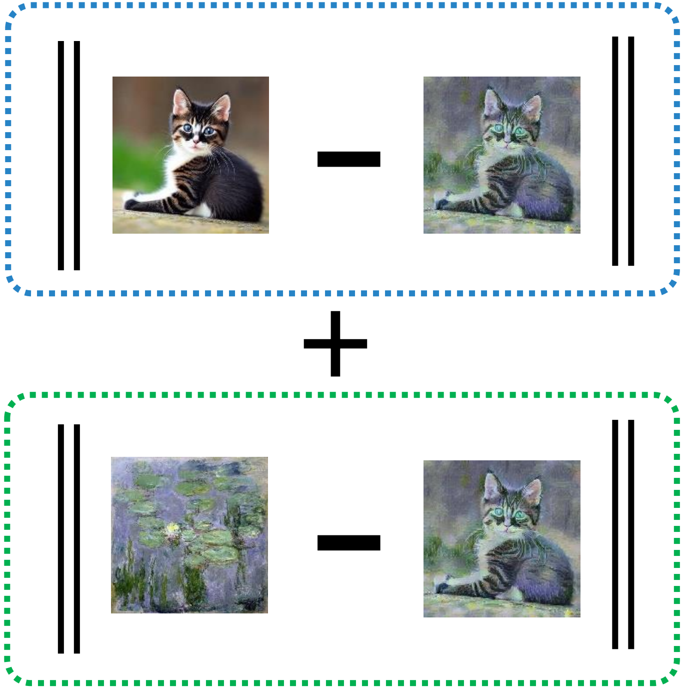
Similarity of style



Style Transfer without Neural Networks

Similarity of content

Similarity of style



Speed ↓

Computation ↑

Derivation of Neural Style Transfer

$$I^* = \arg\min_{I} \mathcal{L}_{total}(I_c, I_s, I) = \arg\min_{I} \ \alpha \mathcal{L}_c(I_c, I) + \beta \mathcal{L}_s(I_s, I),$$

Model-free optimization

$$\theta^* = \arg\min_{\theta} \mathcal{L}_{total}(I_c, I_s, g_{\theta^*}(I_c)), \ \ I^* = g_{\theta^*}(I_c).$$

Model-based optimization

Model-optimization-based NST

$$\theta^* = \arg\min_{\theta} \mathcal{L}_{total}(I_c, I_s, g_{\theta^*}(I_c)), \quad I^* = g_{\theta^*}(I_c).$$

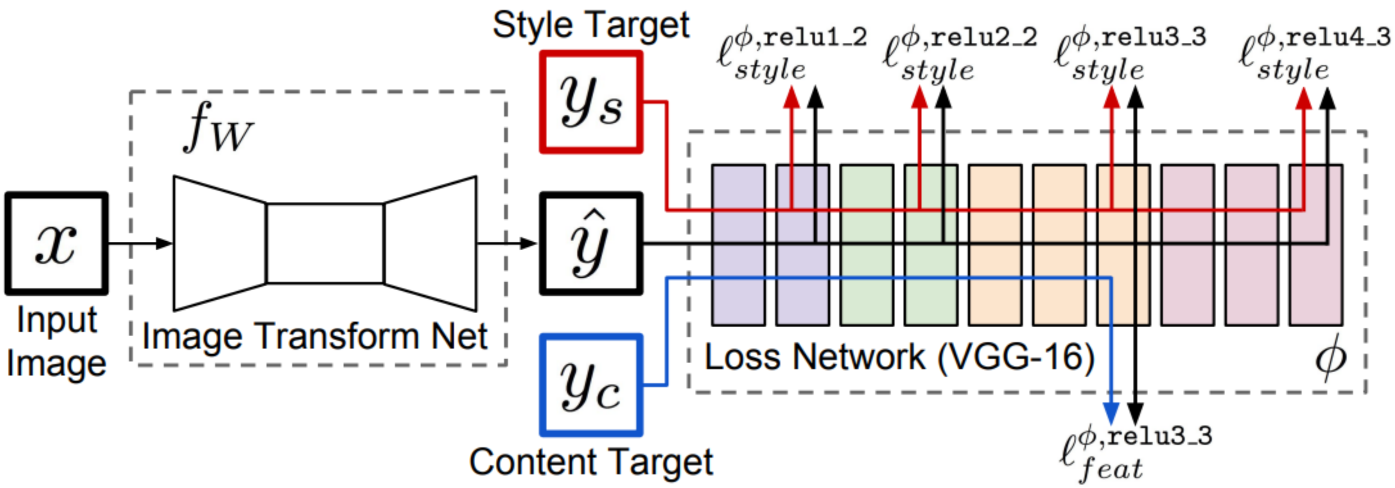
Per-style-per-Model

Multiple-style-per-Model

Arbitrary-style-per-Model

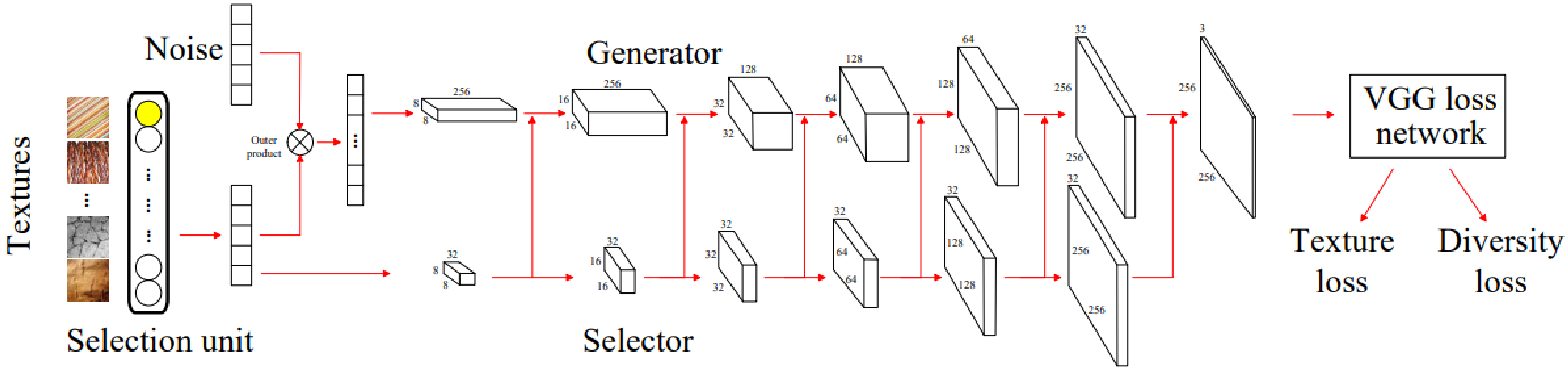
Per-Style-Per-Model (PSPM) Neural Methods

Perceptual Losses for Real-Time Style Transfer and Super-Resolution



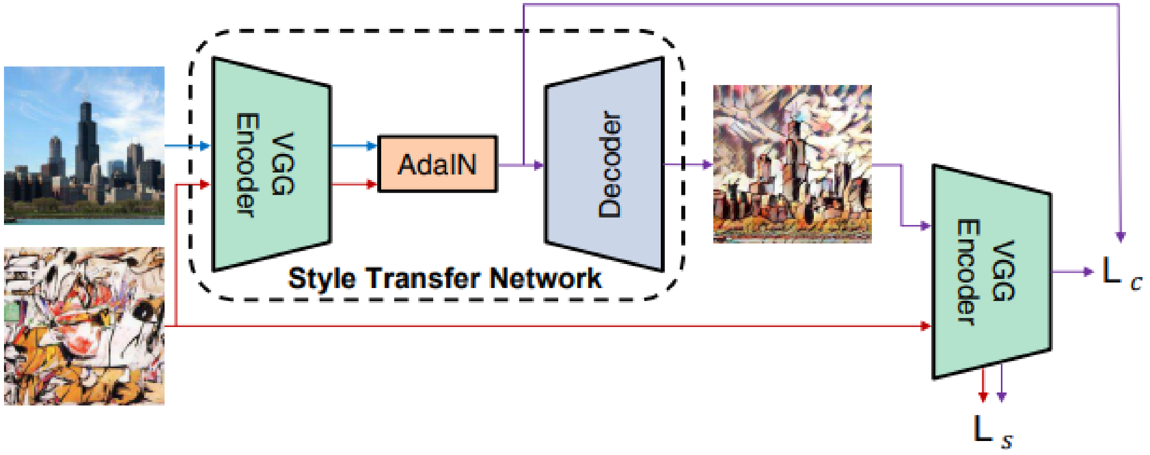
Multiple-Style-Per-Model (MSPM) Neural Methods

Diversified Texture Synthesis with Feed-forward Networks



Arbitrary-Style-Per-Model (ASPM)

Arbitrary Style Transfer in Real-time with Adaptive Instance Normalization



Extensions and Variations of NST

- Doodle Style Transfer [65]
- Stereoscopic Style Transfer [70]
- Portrait Style Transfer [71]
- Video Style Transfer
- Character Style Transfer [78, 79, 80]
- Photorealistic Style Transfer [81, 82]
- Fashion Style Transfer [86]
- Audio Style Transfer [87, 88]

Extensions and Variations of NST

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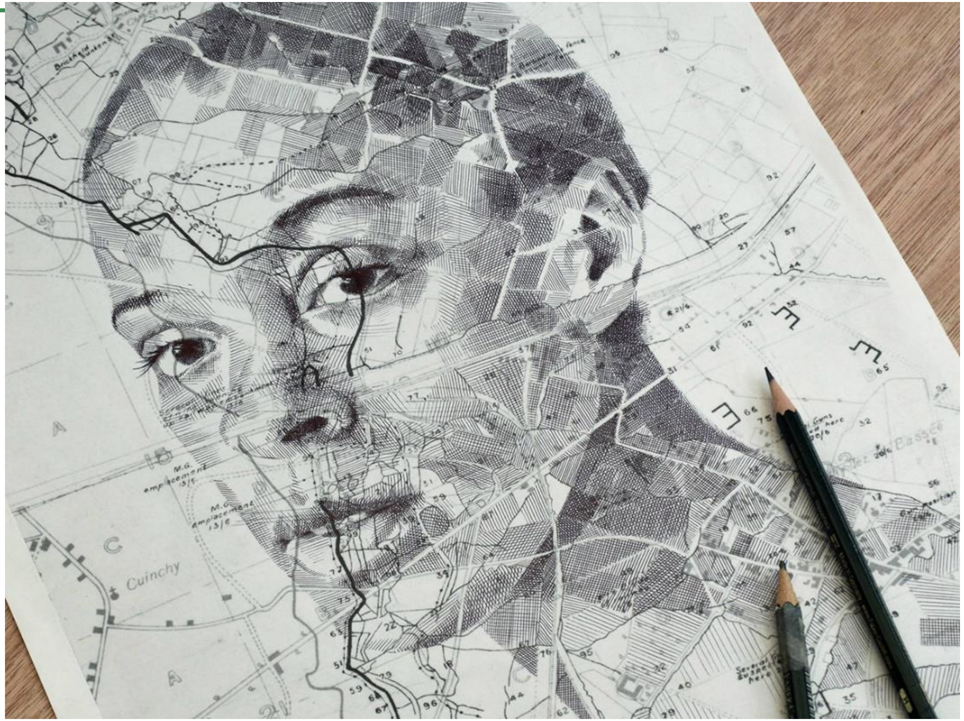
Video style transfer

Painting vs Drawing



Structure-aware Video Style Transfer with Map Art

THI-NGOC-HANH LE, YA-HSUAN CHEN, and TONG-YEE LEE, National Cheng-Kung University, Taiwan, Republic of China

Changing the style of an image/video while preserving its content is a crucial criterion to access a new neural style transfer algorithm. However, it is very challenging to transfer a new map art style to a certain video in which "content" comprises a map background and animation objects. In this article, we present a novel comprehensive system that solves the problems in transferring map art style in such video. Our system takes as input an arbitrary video, a map image, and an off-the-shelf map art image. It then generates an artistic video without damaging the functionality of the map and the consistency in details. To solve this challenge, we propose a novel network, *Map Art Video Network* (MAViNet), the tailored objective functions, and a rich training set with rich animation contents and different map structures. We have evaluated our method on various challenging cases and many comparisons with those of the related works. Our method substantially outperforms state-of-the-art methods in terms of visual quality and meets the mentioned criteria in this research domain.

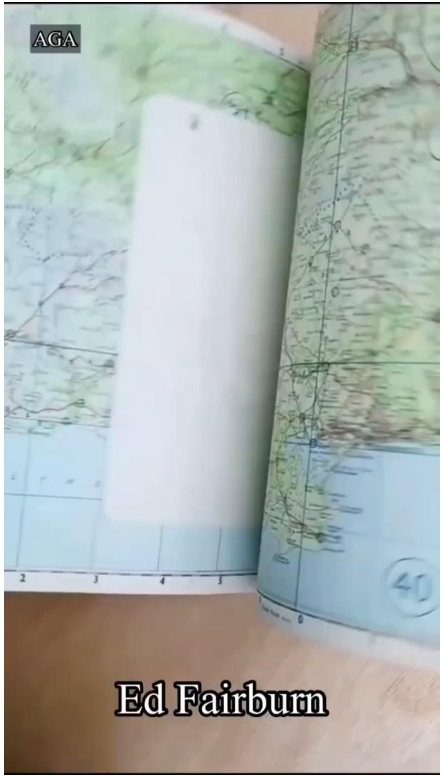
CCS Concepts: • **Computing methodologies** → **Image manipulation;**

Additional Key Words and Phrases: Style transfer video, coherence, map art, CNN, MAViNet

ACM Reference format:
Thi-Ngoc-Hanh Le, Ya-Hsuan Chen, and Tong-Yee Lee. 2023. Structure-aware Video Style Transfer with Map Art. *ACM Trans. Multimedia Comput. Commun. Appl.* 19, 3s, Article 131 (February 2023), 25 pages.
https://doi.org/10.1145/3572030

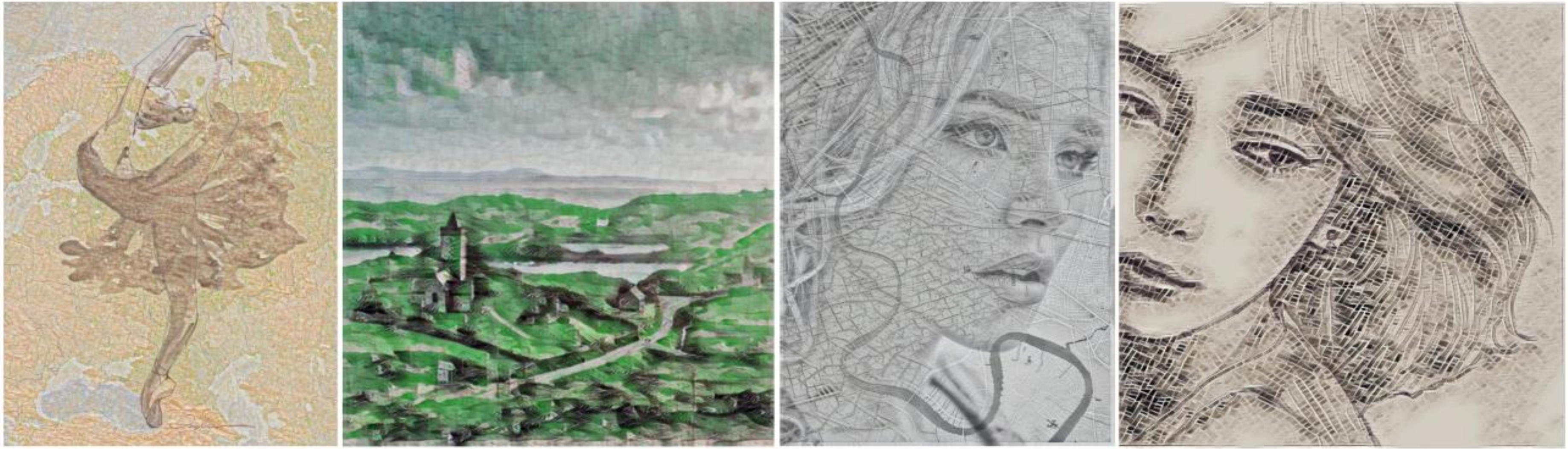
Video style transfer with map art

Map art is a masterpiece in which the artist integrates human portrait and topography to make it appear as though the two have always **belonged together**.



Source: Youtube

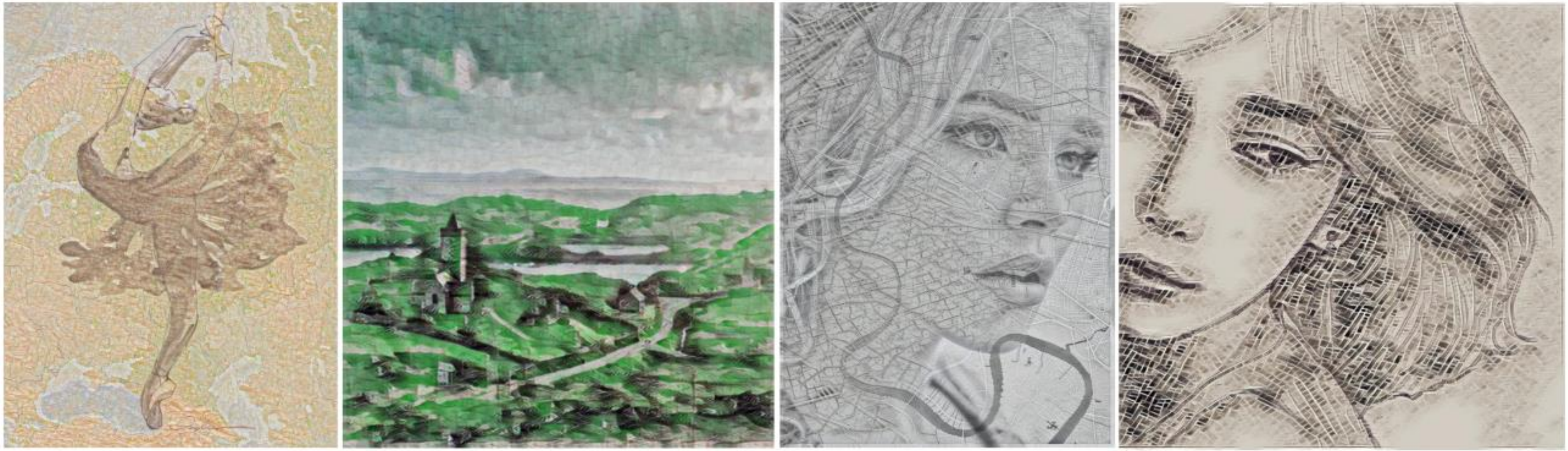
Video style transfer with map art



Map art by ours

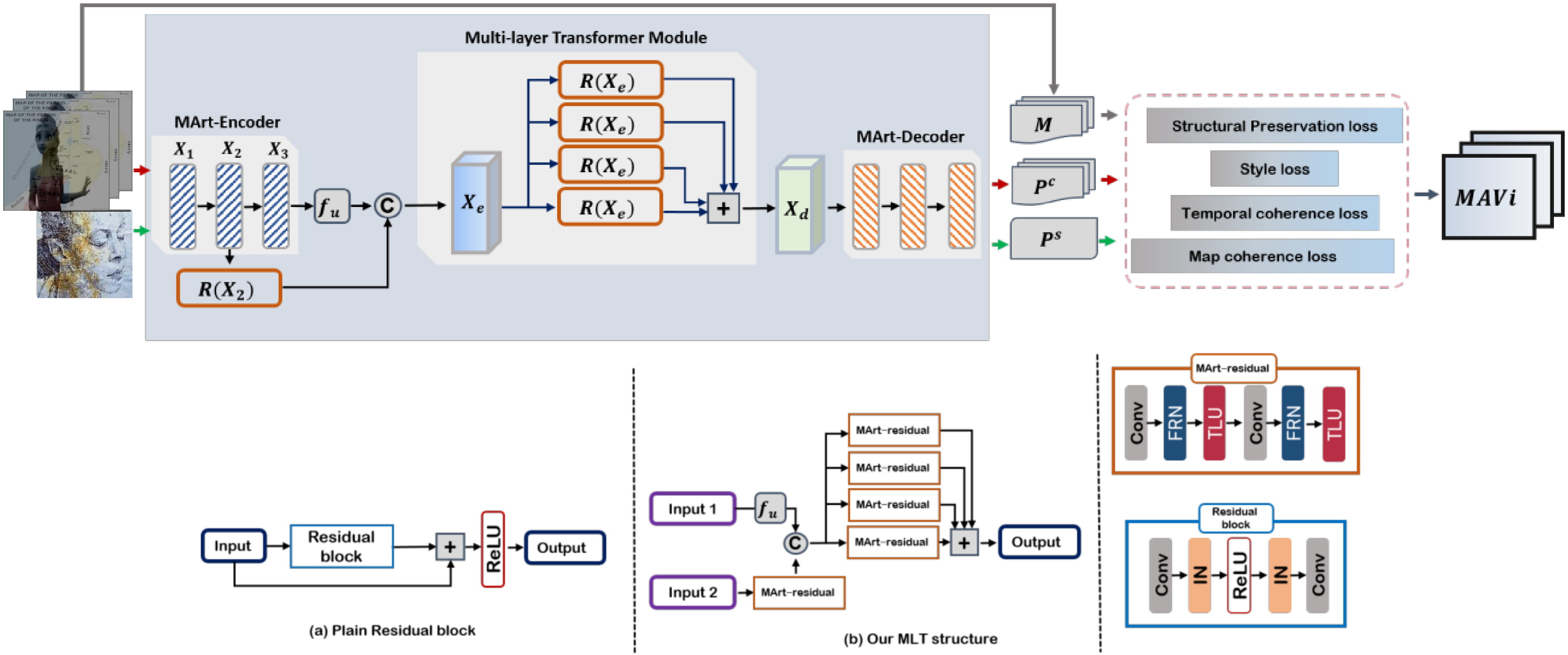
Map art by artists

Challenges



- Transferring the pencil style
- Preserving intensity attributes of background
- Temporal coherency

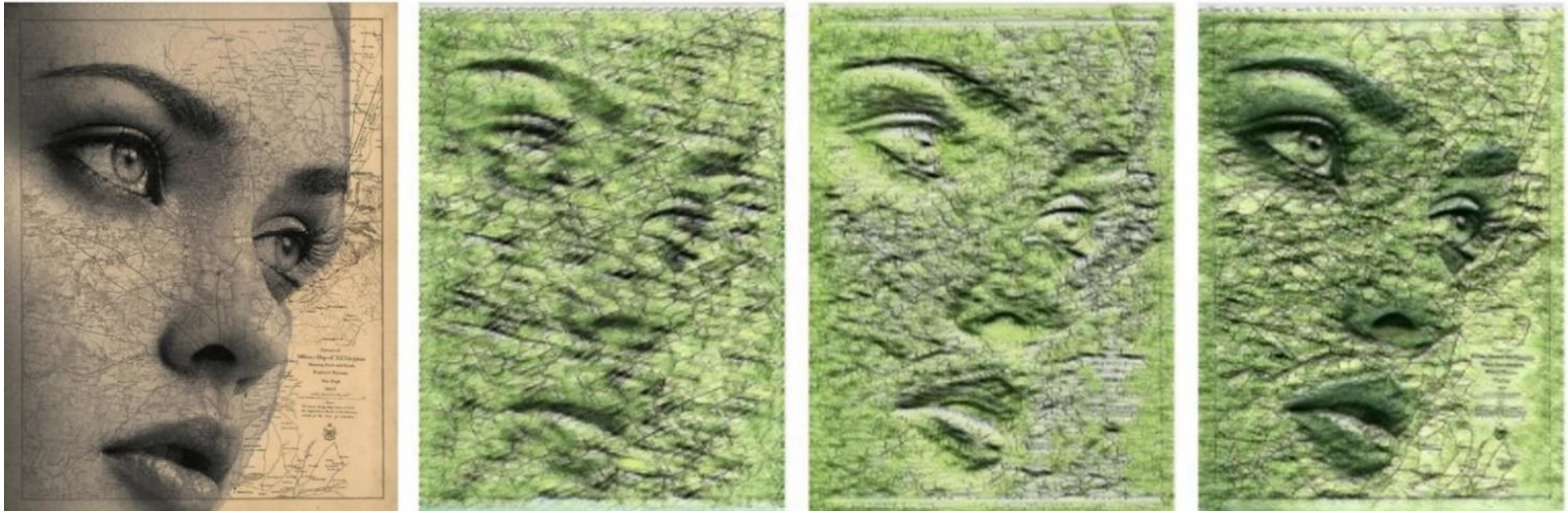
Map art style transfer video



(a) Plain Residual block

(b) Our MLT structure

Ablated Results of MLT module



With convolution layers

With plain residual block

With MLT module

Loss function

$$\min_{f} \left(\lambda_{SP}\mathcal{L}_{SP}(f) + \lambda_{S}\mathcal{L}_{S}(f) + \lambda_{CH}\mathcal{L}_{CH}(f) + \lambda_{TV}\mathcal{L}_{TV}\right)$$

Structural preservation

MArt style

Coherence

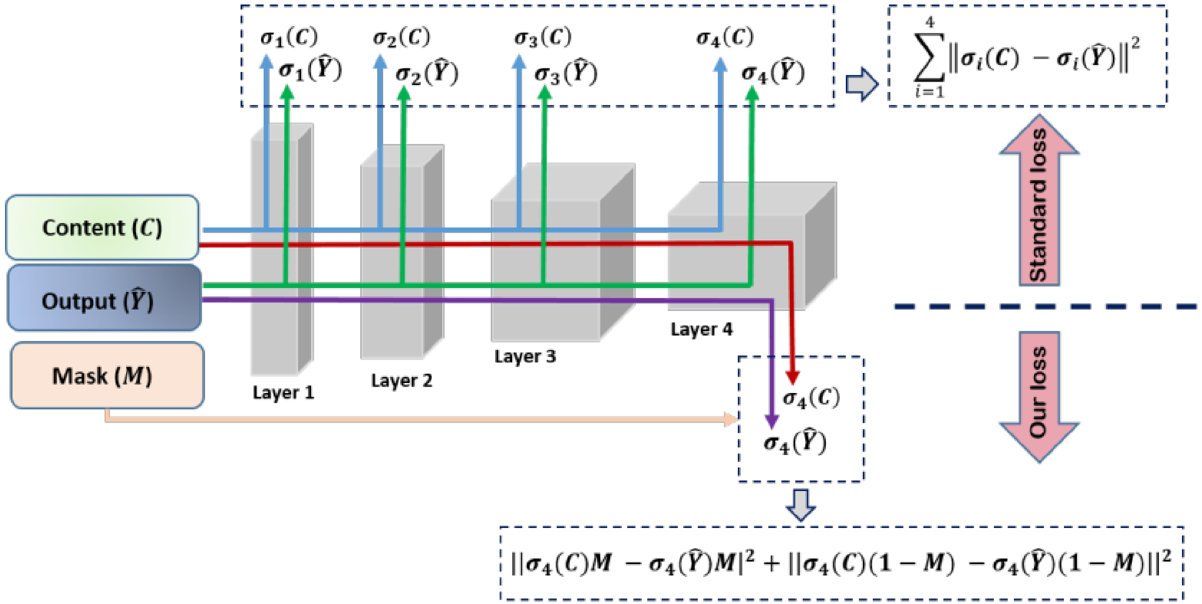
Total variation

Structural preservation loss

Structural preservation = Background Preservation $\mathcal{L}_b$ + Foreground Preservation $\mathcal{L}_f$

$$\mathcal{L}_b = \|\Phi(\mathcal{C})(1-\mathcal{M}) - \Phi(\hat{\mathcal{Y}})(1-\mathcal{M})\|^2$$

$$\mathcal{L}_f = \|\Phi(\mathcal{C})\mathcal{M} - \Phi(\hat{\mathcal{Y}})\mathcal{M}\|^2$$

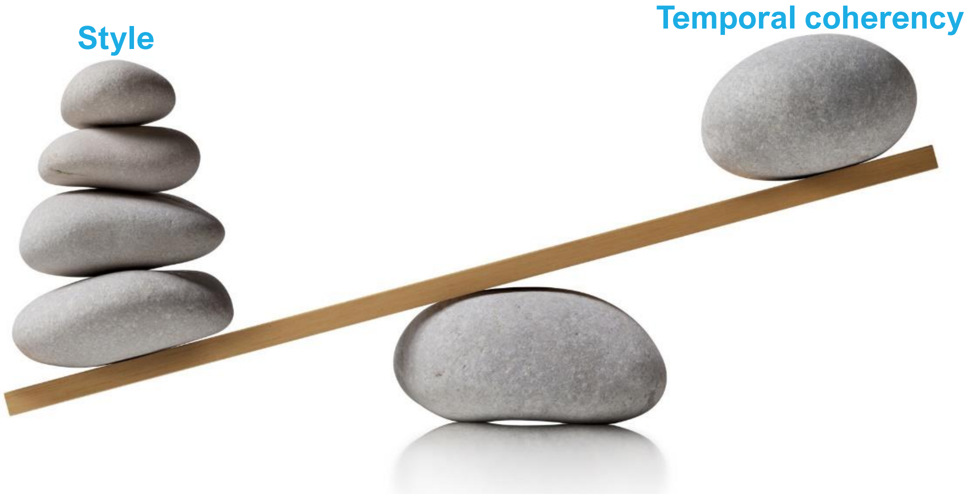


Ablated results of structural preservation loss

Input | Without $\mathcal{L}_{SP}$ | With $\mathcal{L}_{SP}$

Coherence loss

Coherence Loss = Map coherency $\mathcal{L}_m$ + Temporal coherency $\mathcal{L}_t$

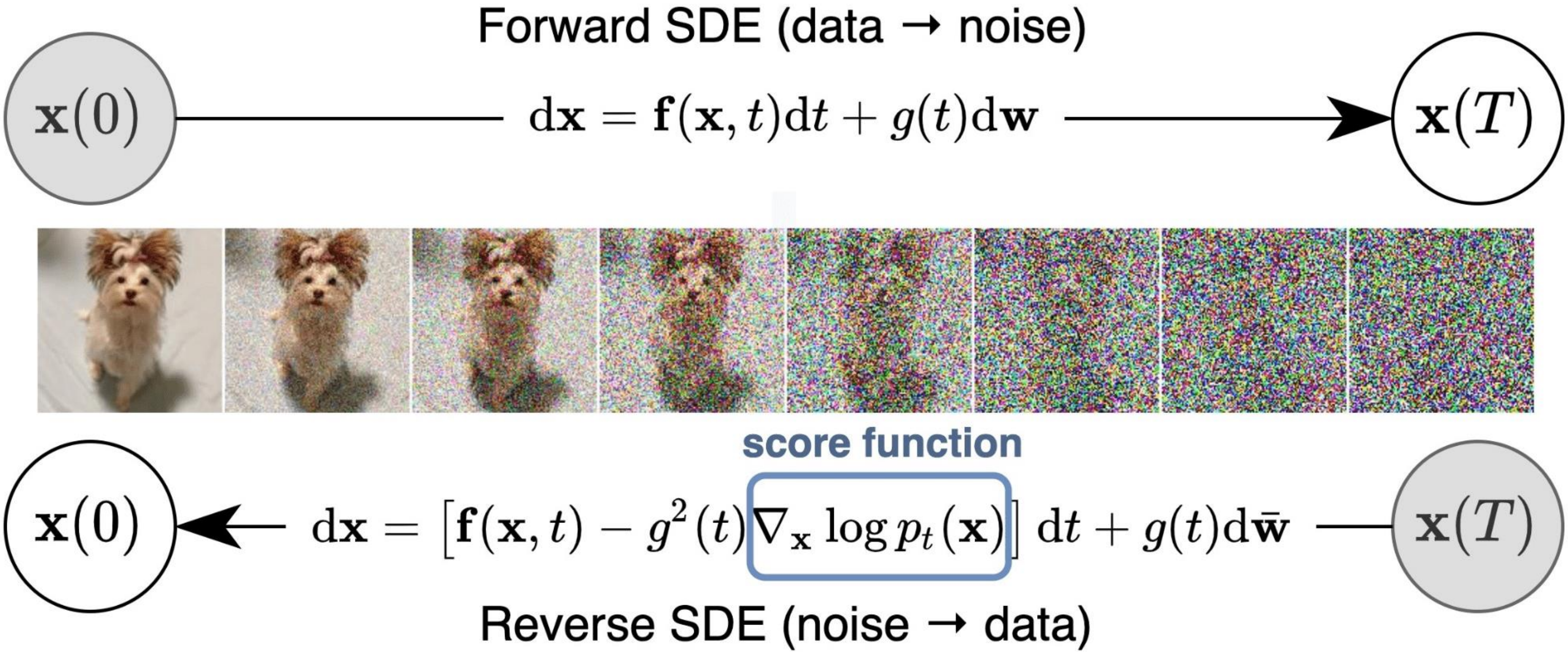


Stylizing video with Map art style

Stylizing video with Map art style

New generation of Style Transfer has come …

Diffusion-based style transfer



Diffusion-based style transfer

Portrait of a woman stylized with Renaissance art

Input image

Input promt

Generated image

Diffusion-based style transfer

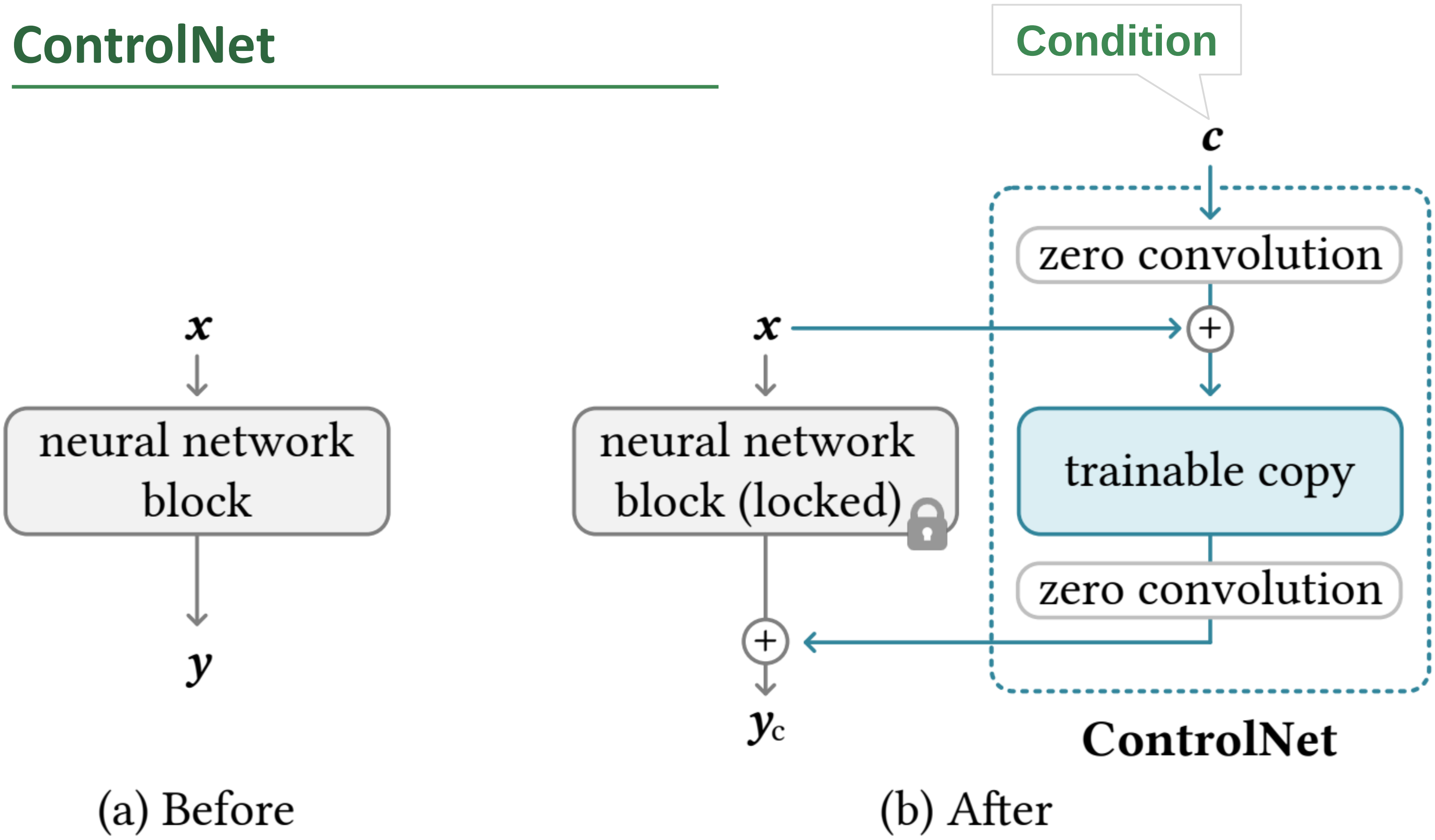
Portrait of a woman stylized with Renaissance art

Challenging to control the result

Diffusion-based style transfer

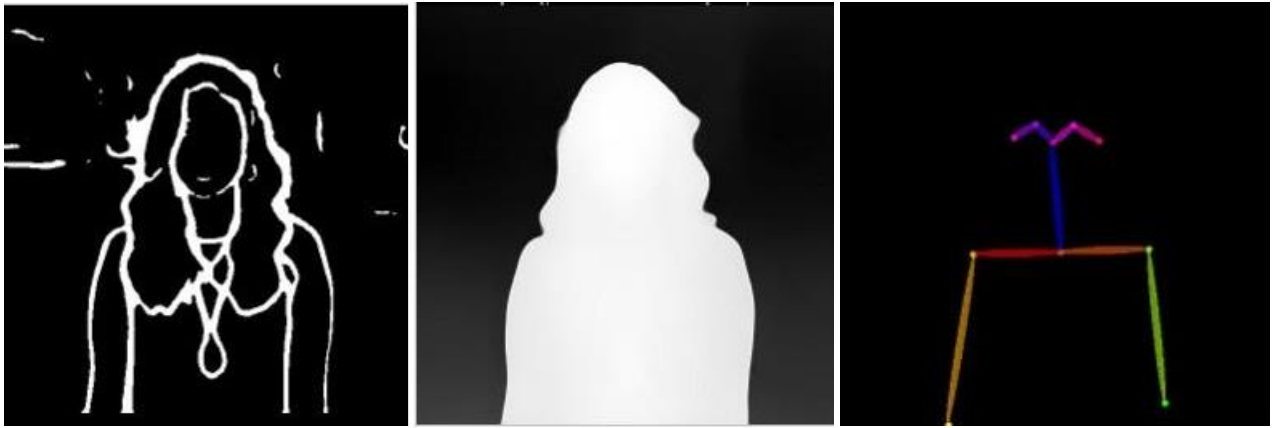
Portrait of a woman stylized with Renaissance art

ControlNet


Condition
c
zero convolution
x
neural network block
y
x
neural network block (locked)
trainable copy
zero convolution
y c
ControlNet
(a) Before
(b) After

ControlNet

Input image



Various kinds of condition

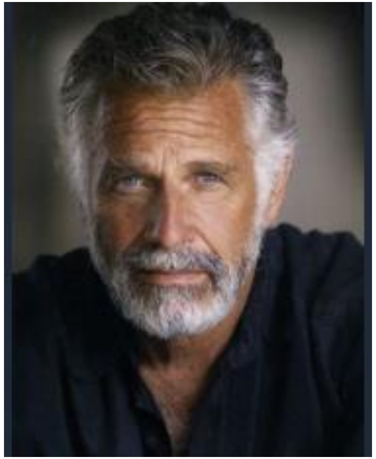
ControlNet

Prompt:
“Room"

ControlNet

Prompt:
"Chief in the kitchen"

ControlNet



Prompt: "oil painting of handsome old man, masterpiece"

Potential Future work

Not imitate but **create new** form

of AI-created Art!

End.

Hope you enjoy!