Image Synthesis
Part 1. Texture Synthesis and Style Transfer
Style Transfer

Content image

Style image

Output image
Early Approaches for Texture Synthesis

Painterly Rendering (SIGGRAPH’98)

Source image  Rough sketch  Intermediate sketch  Final painting

Image Analogies (SIGGRAPH’01)

$A$  $A'$  $B$  $B'$

“Painterly Rendering with Curved Brush Strokes of Multiple Sizes.” Aaron Hertzmann. SIGGRAPH 1998.

Early Approaches for Texture Synthesis

Image Quilting (SIGGRAPH’01)

Texture Synthesis with Neural Networks: Gram Matrix

Each layer of CNN gives $C \times H \times W$ tensor of features; $H \times W$ grid of $C$-dimensional vectors. Efficient to compute; reshape features from $C \times H \times W$ to $F = C \times HW$

Outer product of two $C$-dimensional vectors gives $C \times C$ matrix of elementwise products.

Average over all $HW$ pairs gives **Gram Matrix** of shape $C \times C$ giving unnormalized covariance.

then compute $G = FF^T$
Beyond Color and Texture Transfer

Content

Style

Stylized Output

Geometry Transfer via Correspondences

“Neural Best-Buddies: Sparse Cross-Domain Correspondence.”
Kfir Aberman, Jing Liao, Mingyi Shi, Dani Lischinski, Baoquan Chen and Daniel Cohen-Or. SIGGRAPH 2018.
Deformable Style Transfer

\[
L(X, \theta, I_c, I_s, P, P') = \alpha L_{content} (I_c, X) \\
+ L_{style} (I_s, X) + L_{style} (I_s, W(X, \theta)) \\
+ \beta L_{warp} (P, P', \theta) + \gamma R_{TV} (\theta)
\]

Parameters

Stylization \( X \)
Deformation \( \theta \)
Warped stylized image \( W(X, \theta) \)

Deformable Style Transfer

Part 2. Image Synthesis with Generative Models
Figure 11 from "Analyzing and Improving the Image Quality of StyleGAN." Tero Karras, Samuli Laine, Miika Aittala, Janne Hellsten, Jaakko Lehtinen, Timo Aila. CVPR 2020.
Generative Adversarial Network (GAN)

\[
\min_G \max_D \mathbb{E}_{x \sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z \sim p_z(z)}[\log(1 - D(G(z)))]
\]

Figure from "LOGAN: Membership Inference Attacks Against Generative Models." Jamie Hayes, Luca Melis, George Danezis, Emiliano De Cristofaro. PoPETs 2019.
(Left) Figure 12 from “Analyzing and Improving the Image Quality of StyleGAN.” Tero Karras, Samuli Laine, Miika Aittala, Janne Hellsten, Jaakko Lehtinen, Timo Aila. CVPR 2020.

(Right) Figure 1 from "GANSpace: Discovering Interpretable GAN Controls." Erik Härkönen, Aaron Hertzmann, Jaakko Lehtinen, Sylvain Paris. arXiv 2020.
Part 3. Image Synthesis for Fair Visual Recognition
Bias in Recognition Systems


(Right) Figure 1 from "Does Object Recognition Work for Everyone?" Terrance DeVries, Ishan Misra, Changhan Wang, Laurens van der Maaten. CVPRW 2019.

Amazon Rekognition Performance on Gender Classification

98.7% 68.6% 100% 92.9%

DARKER MALES DARKER FEMALES LIGHTER MALES LIGHTER FEMALES


(Right) Figure 1 from "Does Object Recognition Work for Everyone?" Terrance DeVries, Ishan Misra, Changhan Wang, Laurens van der Maaten. CVPRW 2019.
Image Synthesis for Fair Visual Recognition

“Fair Attribute Classification through Latent Space De-biasing.” Vikram V. Ramaswamy, Sunnie S. Y. Kim, Olga Russakovsky. (Work in progress)
Is that video real?
Fake images and videos are everywhere. Here’s how to spot them.

By A.J. Willingham, CNN
Published October 19, 2020

A deepfake bot is being used to “undress” underage girls
A technology similar to DeepNude, the 2019 app that shut down shortly after launch, is now spreading unfettered on Telegram.

Deepfake Detection Challenge Results: An open initiative to advance AI
June 12, 2020

https://ai.facebook.com/blog/deepfake-detection-challenge-results-an-open-initiative-to-advance-ai/
https://www.wired.com/story/deepfakes-getting-better-theyre-easy-spot/