Style Transfer

Team Athenians

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Overview

Objectives

- Transfer any arbitrary visual styles to content images (Style Transfer)
- Allow user control on the amount of stylization.

Challenges

Preserving the actual content of the image, efficiency, quality of the output images

Universal Style Transfer via Feature Transforms

Li, Y., Fang, C., Yang, J., Wang, Z., Lu, X., & Yang, M. H. (2017).

arXiv preprint arXiv:1705.08086.

The paper Universal Style Transfer via Feature Transforms applies feature transforms like whitening and coloring which are further embedded to an image reconstruction network in order to perform style transfer on images.

Goal

Content

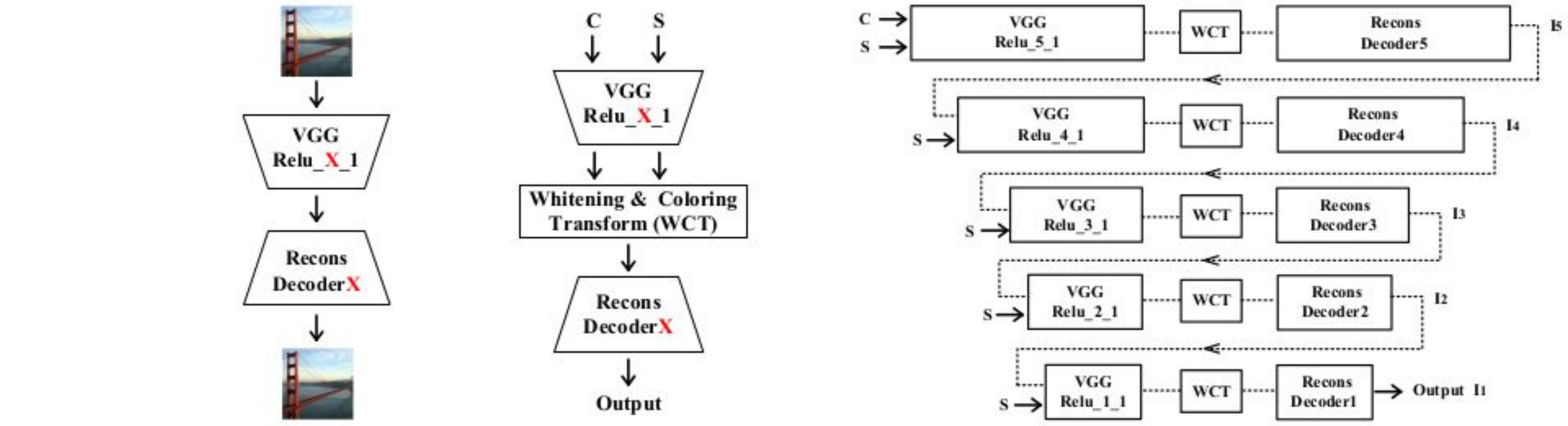
Style

Resultant image

Methodology

- The paper proposes to use **feature transforms**: whitening and coloring to directly match content feature statistics to those of a style image.
- The feature transforms are coupled with a pre-trained general encoder-decoder network, so that the transfer is done via feed-forward operations.
- Thus they do style transfer via an image reconstruction process coupled with feature transformations as above.
- The reconstruction part is responsible for inverting features back to the RGB space and the feature transformation matches the statistics of a content image to a style image.

Pipeline



(a) Reconstruction (b) Single-level stylization (c) Multi-level stylization

Pipeline (contd.)

- Pre-train five decoder networks Decoder (X=1,2,...,5) through image reconstruction to invert different levels of VGG features.
- With both VGG and Decoder X fixed, and given the content image C and style image S, perform the style transfer through whitening and coloring transforms.
- Extend single-level to multi-level stylization in order to match the statistics of the style at all levels.
- The result obtained by matching higher level statistics of the style is treated as the new content to continue to match lower-level information of the style.

Reconstruction Decoder

- VGG-19 used as an encoder.
- Decoder network is trained for inverting VGG features to the original image.
- Designed as being symmetrical to VGG-19 network (up to Relu_X_1 layer), with the nearest neighbor upsampling layer used for enlarging feature maps.
- Pixel reconstruction loss and feature loss are employed for reconstructing an input image.

$$L = \|I_{output} - I_{input}\|_2^2 + \lambda \|\Phi(I_{output}) - \Phi(I_{input})\|_2^2$$

Feature Transforms

Extract vectorized VGG features maps f_c and f_s from content image and style image respectively. Then we apply Whitening and coloring transforms as follows:

Whitening Transform

$$\hat{f}_c = E_c \, D_c^{-\frac{1}{2}} \, E_c^\top \, f_c$$

Where D_c is the diagonal matrix with the eigenvalues of the covariance matrix $f_c \, f_c^\top \in \Re^{C \times C}$,

and E_c is the corresponding orthogonal matrix of eigenvectors, satisfying $f_c \, f_c^\top = E_c D_c E_c^\top$

Coloring Transform

$$\hat{f_{cs}} = E_s \, D_s^{\frac{1}{2}} \, E_s^\top \, \hat{f}_c$$

Where D_s and E_s are calculated in same manner as above.

$$\hat{f_{cs}} = \hat{f_{cs}} + m_s$$

Work done till now....

- Single Level Stylisation
- Modules coded:
  - Dataloader
  - Reconstruction Decoder
  - WCT transforms

Method of Experimentation

- Tried single level stylisation on various style and content images combinations.
- Kept style constant and varied content image.
- Kept content image constant and varied styles.

Results: Single level Style Transfer

Experiment 1

Kept style constant and varied content image.

Content Image

Style

Transformed image

Content Image

Style

Transformed image

Content Image

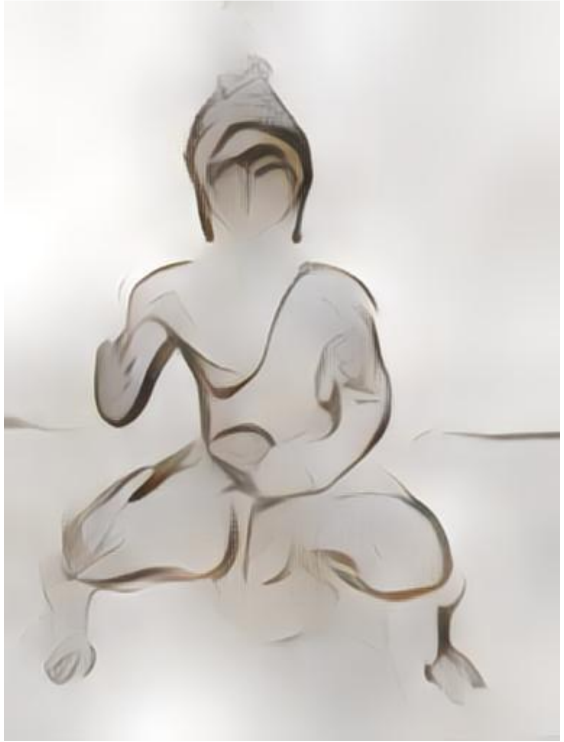
Style

Transformed image

Content Image

Style

Transformed image

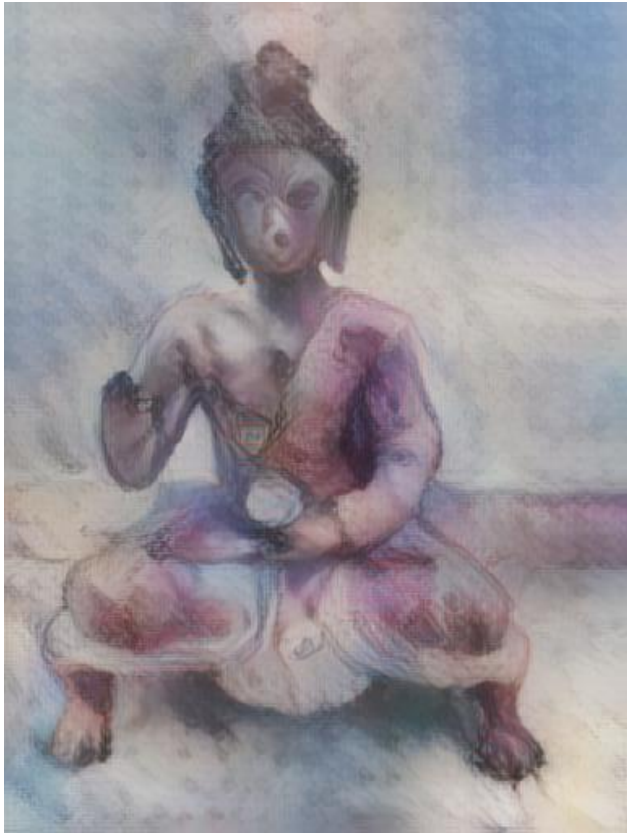


Content Image | Style | Transformed image

Content Image

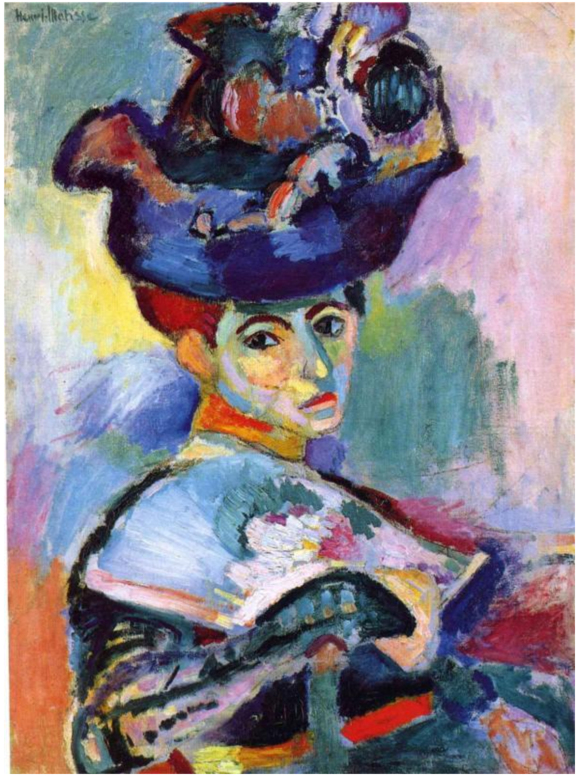
Style

Transformed image



Content Image

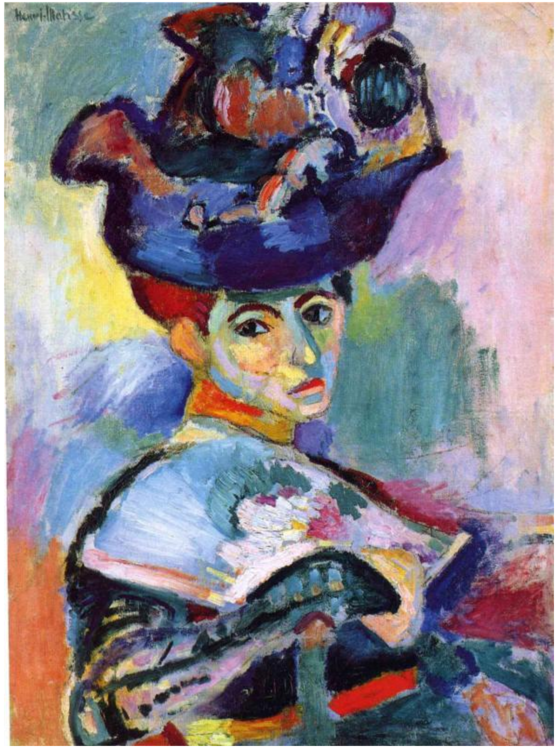
Style



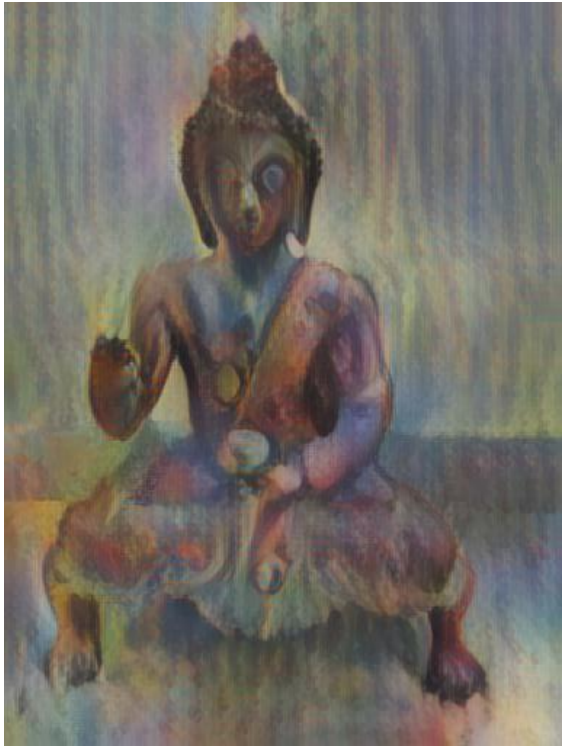
Transformed image

Content Image

Style



Transformed image



Experiment 2

Kept content image constant and varied Style.

Content Image

Style

Transformed image

Content Image

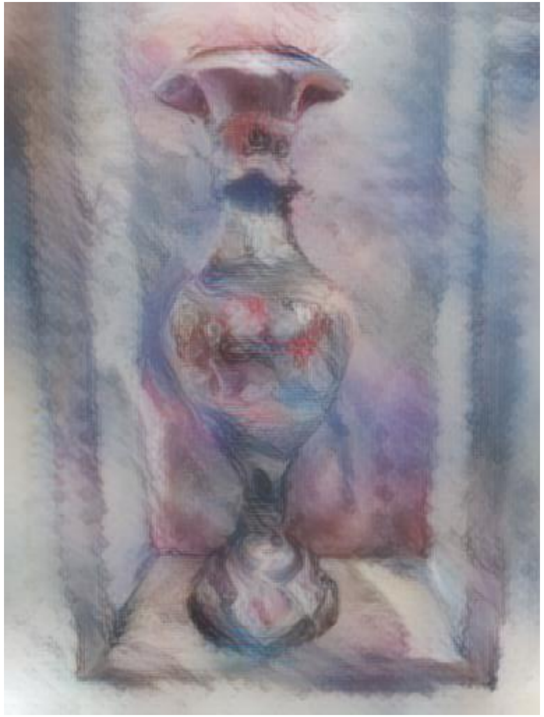
Style

Transformed image

Content Image

Style

Transformed image



Content Image

Style

Transformed image

Content Image

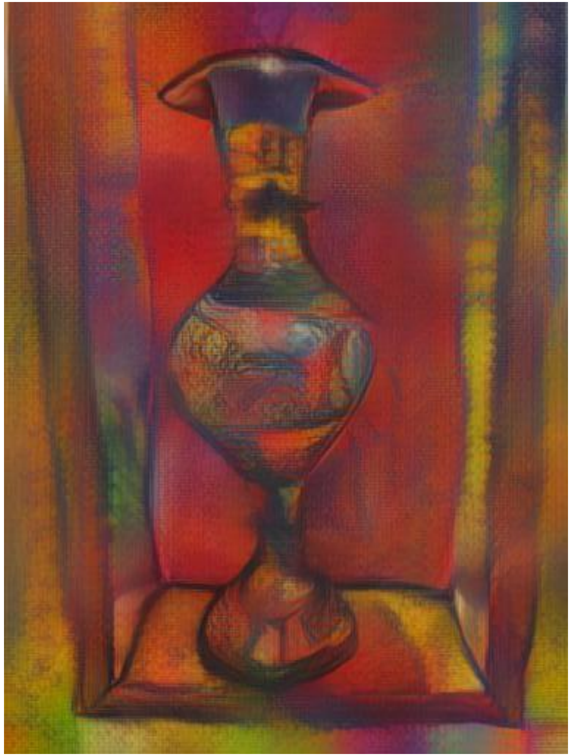
Style

Transformed image

Content Image

Style

Transformed image



Content Image

Style

Transformed image

Content Image

Style

Transformed image

Next Steps

- Multi-level coarse-to-fine stylization.
- User Controls
  - User can control scale, weight and spatial features of style.
  - Scale can be controlled by varying size of input style image.
  - Weight is controlled by the style weight α in the feed-forward passes
  - Spatial control is provided via masks for specific regions and styles.

Frameworks and Libraries

- Python (Pytorch)
- OpenCV

Thank You!