Art Nouveau Style Transfer with Face Alignment Principal Curves

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Flourished throughout Europe and the United States at the turn of 19th and 20th centuries, Art Nouveau still remains one of the most beautiful decorative art movements. Premeditating the idea of art and design as part of everyday life and inspired by natural forms and patterns of plants and flowers, it has influenced different aspects of art and architecture, such as interior, furnishings and glass design, as well as graphic work, posters, and illustration. This project inspired by Henri de Toulouse-Lautrec and Alphonse Mucha works of art is aimed to develop a deep learning tool transforming already boring photos into a bright and bold Art Nouveau fine art posters.

Data

An example of a style image. Alphonse Mucha paintings obtained from ‘Painter by numbers’ Kaggle competition, 200 in total.

An example of a content image. Images downloaded from Flickr using ‘women, vintage dress’ tag, 2000 in total.

Method

Input: content image C, style image S
Output: generated image G

Features: via VGG-16

- Content \( a_i f(C) \) - output of \( i \)-th activation layer
- Style \( GM(f)(S) \) - gram matrix of layer \( f \), measures the correlation across the channels

Loss:

- Content \( L_{content} = \frac{1}{|a|} \sum_i |a_i f(C) - a_i f(G)|^2 \)
- Style \( L_{style} = \sum_i |GM(f)(C_i) - GM(f)(G)|^2 \)
- Regularization \( TV(G) \)

\( L(G) = \alpha L_{content}(C, G) + \beta L_{style}(S, G) + \gamma TV(G) \)

Hyperparameter Tuning

- Learning rate \( lr = 0.002, 0.05, 0.1 \)
- VGG-16 Layers \( L_c = 1, \ldots, 5 \) and \( L_s = 1, \ldots, 5 \)
- Loss weights \( \alpha = 10^3, 10^4, 10^5, 10^6 \), \( \beta = 1 \) and \( \gamma = 0, 0.1, 300, 3000 \)

Results

Example of face alignment

1. Detect the faces on the content and style images.
2. Pick the face box with the highest confidence value.
3. Create the matrices \( X_{content}, X_{style} \in \mathbb{R}^{2x2} \) containing ‘keypoints’ coordinates.
4. Solve the Procrustes optimization problem: minimize \( \|X_{content} - s \cdot X_{style} R - b\|_F \) w.r.t. \( b, s \) and \( R \).
5. Scale, shift and rotate the content and style images.
6. Crop the images to the same size.

Discussion

- experiment with facial penalty: add pixel-to-pixel penalty measuring the deviation of \( G \) from \( C \)
- add regularization, e.g. adapt Fast Neural Style Transfer
- try Markov Random Fields approach to encode stylistic features

References