Neural Style Transfer for Faces

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***Abstract*—Style transfer is an optimization technique used to take two images, a content image and a style reference image, and blend them together so that the output image looks like the content image, but "painted" in the style of the style reference image. The difference between normal image style transfer and portrait style transfer is that head portraits are sensitive to the slightest irregularities. Balancing the style and portrait features are the ultimate goal of this project. In the normal style transfer, the generic techniques will bring the deformation of the facial structures and features. Due to the limits of the applicability of the traditional method, we are implementing a new way for transferring the painting from a head portrait onto another. We used the Convolutional Neural Networks to reduce the distance between the goal image and the input image iteratively. In our approach, the input identity will be maintained as much as possible, in addition, the facial deformation will be largely reduced.**

I. Introduction

An artistic journey as a portrait painter is often complicated, hard since it has strong sense of details. It is often said - the fact that a good portrait is hard to achieve is a great reason to try painting one in the first place. The most traditional way of painting is, when a subject is sitting in front of an artist. But with the advancements there have been multiple more convenient ways of creating portrait style for a subject. Painting transfer technique can be a great way of creating visual art on its own, utilizing deep learning space. Gatys et al introduced 'A Neural Algorithm of Artistic Style' [2] which used an artificial system based on a Deep Neural Network that creates artistic images of high perceptual quality. However his algorithm is more of a generic side and hence leads to poor capturing of the painting texture and generates irregularities. Selim et al in his paper, 'Painting Style Transfer for Head Portraits using Convolutional Neural Networks' [1] presents the latest technique for head portrait painting transfer. Given an input photograph and an example portrait painting, a new painting is generated that follows the example style. We have drawn inspiration from this paper and have been able to transfer a strong texture of painting style to the input image, while maintaining its original features. As suggested in paper we have used Gatys formulation to transfer the painting textured and have applied gain maps on VGG features.

II. Related Work

The painting style transfer techniques can be mainly classified into three categories: stroke based, texture transfer based and parts transfer. In the stroke based method, the painting will be rendered by simulating the brush stroke placement process. The different attributes like scale, orientation, color and opacity often guide this process. The texture transfer based modifies the input image in a way to follow sample textures. Parts transfer based techniques are based on parsing the input image into different parts. For the style reference image, feature representations are extracted from multiple layers at different scales. In the iteration process, the content loss is the difference between the generated image and the content image, while the style loss between the generated image and the style.

So far limited work exists in head portrait painting. ZHAO and ZHU in their work 'Portrait painting using active templates. In Non-Photorealistic Animation and Rendering' , based their work on image analogies. They present an example-based method to render portrait paintings from photographs, by transferring brush strokes from previously painted portrait templates by artists. . Wang in his paper ' Learnable Stroke Models for Example-based Portrait Painting', presents an algorithm for stylizing photographs into portrait paintings composed of curved brush strokes. He evaluates style transfer between a variety of training and test images, demonstrating a wide gamut of learned brush and shading styles. But in both of these contributions , we need the original unpainted version of the example image, hence the domain applicability gets limited . Salem in his paper, 'Painting Style Transfer for Head Portraits using Convolutional Neural Networks' has presented some great results . He has performed transfers the painting style, using convolutional neural network approach with novel spatial constraints , this conserves the features of face in input image

III. Contribution / Method

We have implement the algorithm used by Salem in his paper, 'Painting Style Transfer for Head Portraits using Convolutional Neural Networks'. First we align the example painting on the input photograph. For this, we extracted the landmarks from the portriat using a pre-built detector and preformed Delaunay triangulation on these landmark points. We warped the Delaunay triangles made from landmark points of the example image to those of the input image using a series of affine transformations. This similar to how it was first done in [3]. This imposes spatial constraints during painting transfer and prevents facial deformation. We then generate feature map for both input image and example image from VGG. We modify input features using Gain maps to transfer the local

Fig. 1. Landmarks on sample image

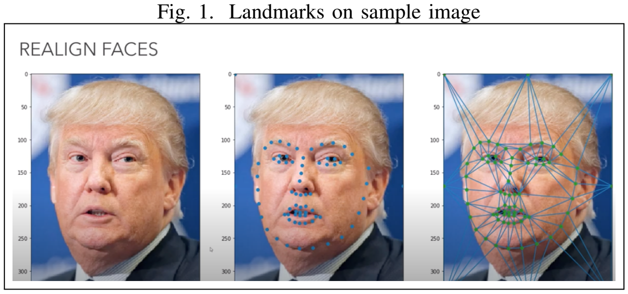
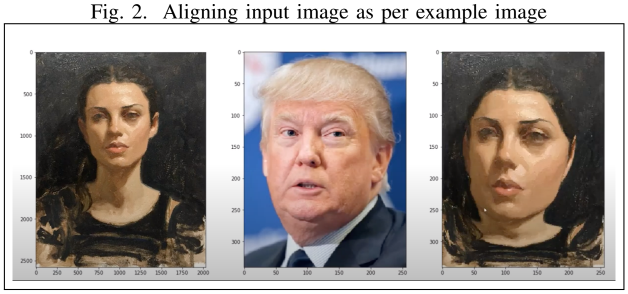


Fig. 2. Aligning input image as per example image



color distributions of the example painting E onto the input photograph I.

After generating modified feature maps from the image we minimise the below equation .

We minimize this equation iteratively until we reach a maximum number of iterations. In our project we have taken maximum no. of iterations as 300. In the equation above F[O] represents VGG features of the desired output painting O. Alphas and betas is 0.5 each for layers 'block3conv1' and 'block4conv1'. Using this equation over gatys algorithm we are able to better capture the texture of the painting styles and preserve the identity of the input photograph.

IV. Results

Following are our results . We used a variety of input images and example portraits. Our results although not extremely precise but are very similar to results shown by Selim. They do better capture the texture of example potrait while preserving the features of the input image.

Fig. 3. Gain Maps

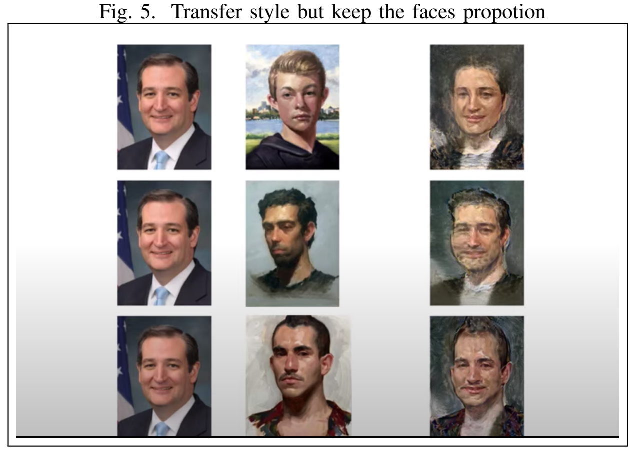
$$F_l[M] = F_l[I] \times G_l,$$

$$G_l = \frac{F_l[E]}{F_l[I] + \epsilon},$$

Fig. 4. Equation is minimized iteratively using feed-forward and back-propagation

$$\mathcal{L}_{\text{total}} = \sum_{l=1}^{L}\left(\alpha_l \frac{1}{2N_l D_l}\sum_{ij}(F_l[O]-F_l[M])^2_{ij}\right)$$
$$+\,\Gamma\sum_{l=1}^{L}\left(\beta_l \frac{1}{2N_l^2}\sum_{ij}(F_l[O]F_l[O]^T - F_l[E]F_l[E]^T)^2_{ij}\right)$$

Fig. 5. Transfer style but keep the faces propotion



The ghosting that we see in some parts on the output might be because of optimization function. More experiements with different optimization hyperparameters may lead to better results.

References

[1] A. Selim, and M. ElgharibN, 'Painting Style Transfer for Head Portraits using Convolutions Neural Networks," 2016.

[2] L. Gatys, A. Echer, and M. Bethge, 'A neural Algorithm of Artistic Style," 2015.

[3] B. Thaddeus, 'Feature-Based Image Metamorphosis," 1992.