Application of image style transfer to unfinished paintings

Tung-Fu Lin
National Taiwan University, No. 1, Sec. 4, Roosevelt Rd., Taipei 10617, Taiwan (R.O.C.);
Dept. of Biomechatronics Engineering

ABSTRACT

This research aims to explore the application of image style transfer techniques to renowned unfinished paintings, focusing on realizing the unrealized works of famous artists throughout history. Image style transfer is a deep learning image processing technique that, through model training, enables the transformation of images into different artistic styles, opening up possibilities for artificial intelligence in the realm of artistic creation.

Keywords: image transformation, style transfer, deep learning, artificial intelligence

1. INTRODUCTION

Image style transfer is an innovative technique in computer vision and deep learning, revolutionizing visual aesthetics. It involves transforming images by applying the artistic style of one image onto the content of another. This process, driven by sophisticated neural networks, enables the fusion of diverse artistic expressions, offering a novel way to create visually stunning and unique compositions, bridging the realms of technology and art.

The primary objectives of this study include: a. Explore the application of style transfer techniques in unfinished paintings, evaluating their transformation effects and potential. b. Implement a concrete style transfer process capable of adapting to various artistic styles. c. Assess and consolidate the strengths and weaknesses of style transfer models, identifying directions for improvement.

We may draw inspiration from mature image style transfer models developed by Google to apply style transfer to unfinished paintings in our study. Testing the model using unfinished works of various renowned artists will validate its effectiveness. We must integrate the analysis of diverse artistic style requirements by testing different artists' works to ensure the model's universality and adaptability.

After applying the developed style transfer model to artworks, we will assess its transformation effects and analyze its pros and cons for further improvement. Through the test results, we will evaluate the model and discuss its strengths, weaknesses, and potential directions for future enhancements.

2. METHODS

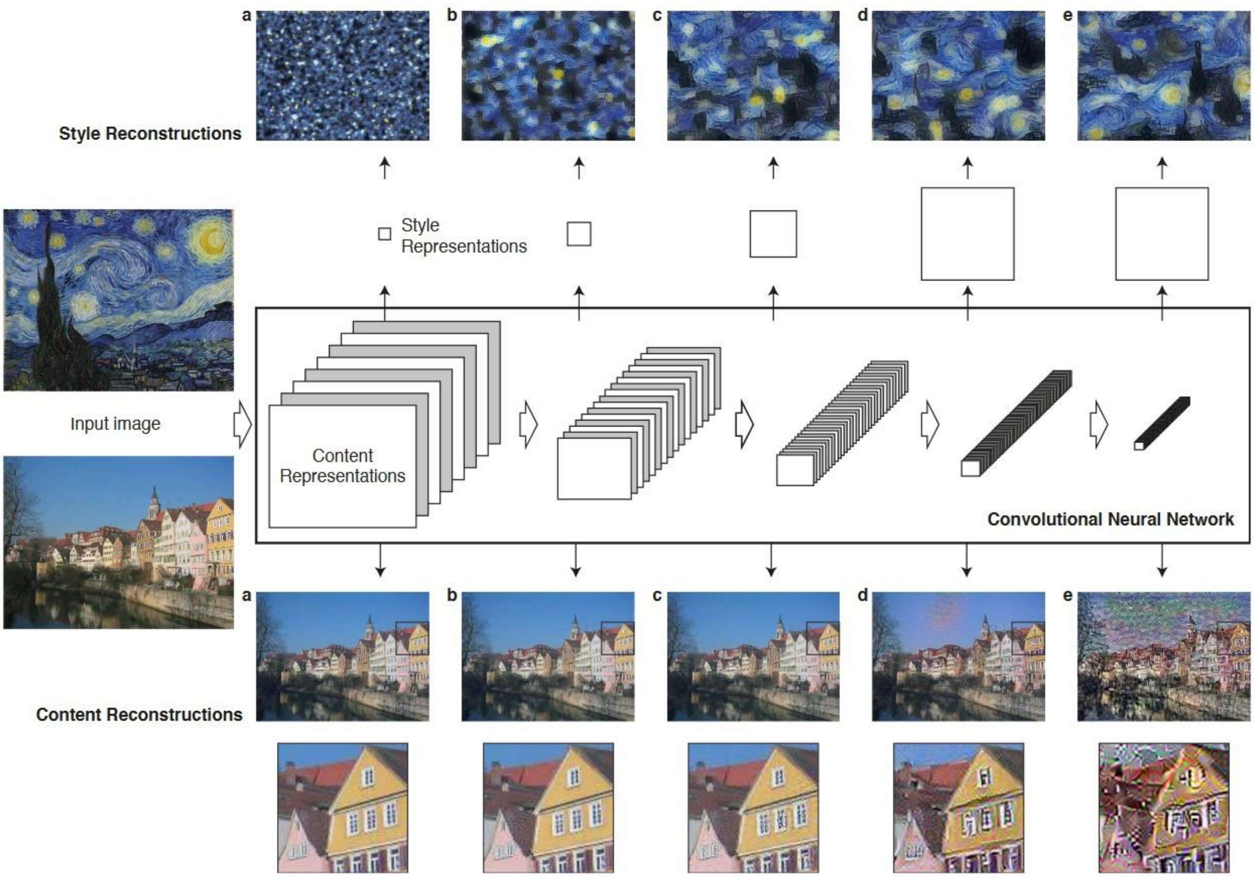
Image artistic style transfer is typically defined as creating a stylized image from a content image and a style image. The content image is usually a photograph, while the style image is often a painting. The neural network algorithm for artistic style defines the content and style of an image as follows:

- Two images are considered similar in content if their high-level features, extracted by an image recognition system, are close in Euclidean distance.

- Two images are considered similar in style if their low-level features, extracted by an image recognition system, share the same spatial statistics.

The first definition is motivated by the observation that the high-level features of pre-trained image classification systems are tuned to semantic information in an image. The second definition is motivated by the hypothesis that a painting style can be regarded as a feature of visual texture. A wealth of literature suggests that repeated patterns representing visual texture can be characterized by low-order spatial statistical features. Images with identical low-order spatial statistical features appear perceptually identical and share a visual texture.

Assuming that a visual texture is spatially homogeneous implies that low-order spatial statistical features can be represented by a Gram matrix expressing the spatially-averaged correlations across filters within a given layer's representation.



3. MATHEMATICAL EQUATIONS

The complete optimization objective for style transfer may be expressed as

$$\min L_c(x, c) + \lambda_s L_s(x, s) \tag{1}$$

where Lc(x, c) and Ls(x, s) are the content and style losses, respectively and λs is a Lagrange multiplier weighting the relative strength of the style loss. We associate lower-level and higher-level features as the activations within a given set of lower layers S and higher layers C in an image classification network.

The content and style losses are defined as

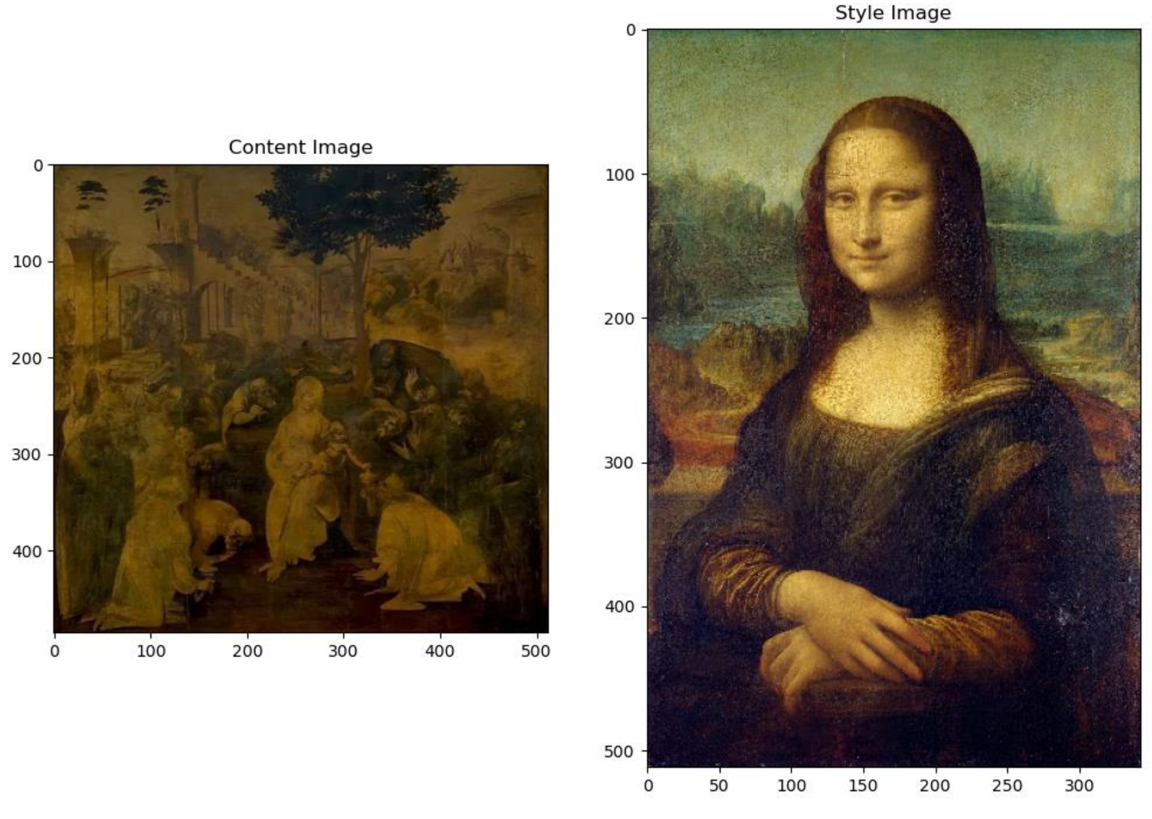
$$\mathcal{L}_s(x, s) = \sum_{i \in \mathcal{S}} \frac{1}{n_i} \mid\mid \mathcal{G}[f_i(x)] - \mathcal{G}[f_i(s)] \mid\mid_F^2 \tag{2}$$

$$\mathcal{L}_c(x, c) = \sum_{j \in \mathcal{C}} \frac{1}{n_j} \mid\mid f_j(x) - f_j(c) \mid\mid_2^2 \tag{3}$$

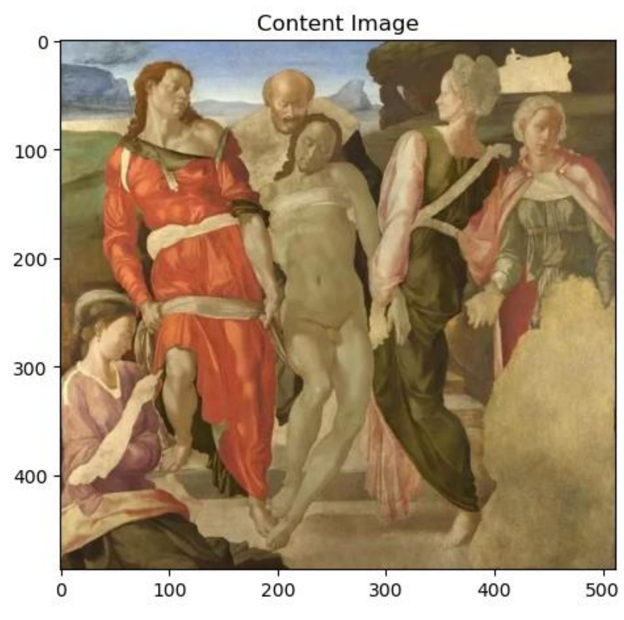
where fl(x) are the network activations at layer l, nl is the total number of units at layer l and G[fl(x)] is the Gram matrix associated with the layer l activations. The Gram matrix is a square, symmetric matrixmeasuring the spatially averaged correlation structure across the filters within a layer's activations.

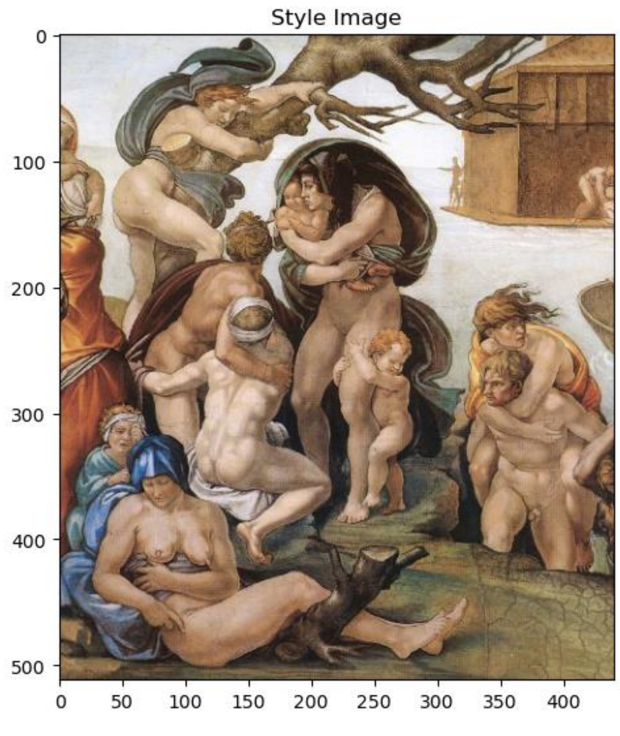
4. RESULTS

Adoration of the Magi Leonardo

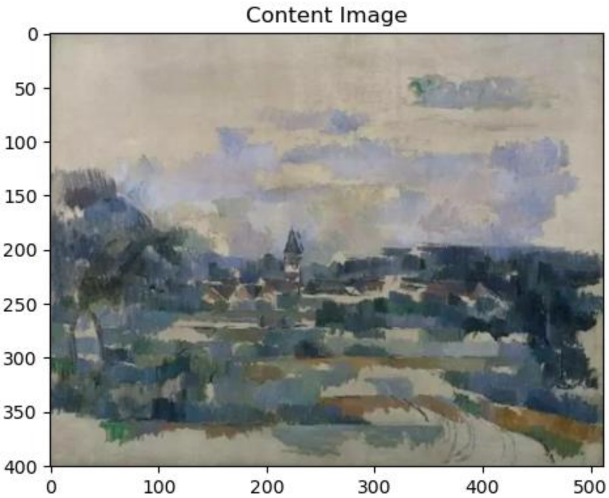


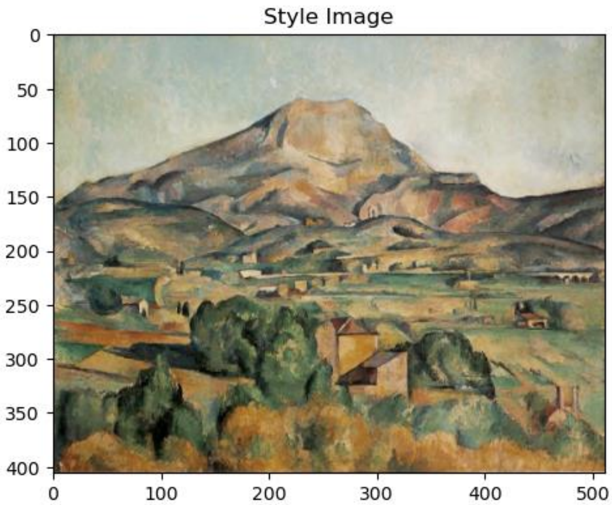
The Entombment Michelangelo





unfinished painting Cézanne





Code link

https://drive.google.com/file/d/185TSa6BIyncl17Jxhgf9Qu5GCmFZPkRu/view?usp=drive_link

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