동양화의 예술적 스타일 탐구

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Exploring the Artistic Style of the Oriental Paintings

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Abstract

Although the work of neural style transfer has shown successful applications in transferring the style of a certain type of artistic painting, it is less effective in transferring Oriental paintings. In this paper, we explore three methods which are effective in transferring Oriental paintings. Then, we take a typical network from each method to carry on the experiment, in view of three different methods to Oriental paintings style transfer effect has carried on the discussion.

Keywords: Style Transfer, CycleGAN, Neural Style Transfer

1. Introduction

In recent years, the amelioration of computational power has allowed machines to begin imitating human behavior. Due to the importance of art, it is no surprise that researchers have begun developing techniques striving to produce unseen creative content. Style transfer, or to repaint an existing photograph with the style of another, is considered a challenging but interesting problem in arts [1].

The Oriental paintings is an ancient art form, in which natural objects are painted with sparse, yet expressive, brush strokes. It consists of diverse styles (e.g, claborate-style painting, Chinese landscape painting, and ink and wash) and has influenced many countries and nations in Eastern and Southeast Asia. It's now a typical symbol of Chinese culture and an important part of the artistic world [3].

Recently, convolutional neural network (CNN) [4] based style transfer methods have shown successful applications in transferring the style of a certain type of artistic painting, e.g, Vincent van Gogh's "The Starry Night", to a real-world photograph, e.g. Transferring the style from one image onto another has become an active topic both in academia [5-9] and industry[10-11] due to the influential work by Gatys et al. [2], where a pre-trained deep learning network for visual recognition is used to capture both style and content representations, and achieves visually stunning results. The generic feature representations learned by high-performing CNN can be used to independently process and manipulate the content and the style of natural images. The hierarchical deep convolutional neural network architecture for fast style transfer designed an associated training scheme that is able to learn both coarse, large-scale texture distortion and fine, exquisite brushwork of an artistic style by utilizing multiple scales of a style image [1].

Unfortunately, current networks often fail to capture small, intricate textures, like brushwork, of many kinds of artworks on high-resolution images. Although the work of neural style transfer has shown promising progress on transferring artistic images with rich textures and colors, e.g., the oil paintings, we observe that it is less effective in transferring Oriental paintings [3].

Unlike western oil paintings which are often concrete and realistic, Chinese traditional freehand painting reveals artistic results of a likeness in spirit rather than in appearance. As a result, different styles of sparse brush strokes are widely utilized to depict different kinds of objects. Thus they are more abstract, texture-less and less colorful. And this abstract style is not captured well by current neural style transfer methods due to lack of corresponding constraints [3]. Different artistic styles may be characterized by exquisite, subtle brushes and strokes, and hence, our observations are that results of these style-transfer networks are often not satisfactory for a large variety of artistic styles, and compare the results of several methods.

In this paper, we explore several methods which are effective in transferring Oriental paintings and compare the results of different methods. The organization of the rest of the paper is as follows: In section 2, three approaches are described: neural style transfer network, semantic style transfer network and CycleGAN. Section 3 shows the experiments and the results. Conclusions are given in Section 4.

2. Related approach

2.1 Neural-Style-Transfer (NST)

By reconstructing representations from intermediate layers of the VGG-19 network, Gatys et al. observe that a deep CNN is capable of extracting image content from an arbitrary photograph and some appearance information from the well-known artwork. Gatys et al. first proposed a new algorithm to capture both style and content representations based on the representations of a pre-trained convolutional neural network [2], derived from their proposed texture modeling technique [13]. However, the approaches fail to capture small, intricate textures and maintain correct texture scales of the artworks.

2.2 Semantic Style Transfer

Given a pair of style and content images which are similar in content, the goal of semantic style transfer is to build a semantic correspondence between the style and content, which maps each style region to a corresponding semantically similar content region. Then the style in each style region is transferred to the semantically similar content region. Here we gave an example in Fig u r e 1. The segmentation map can form a semantic segmentation algorithm [14-15]. Champandard [16] proposed a semantic style transfer algorithm based on the patch-based algorithm [17].

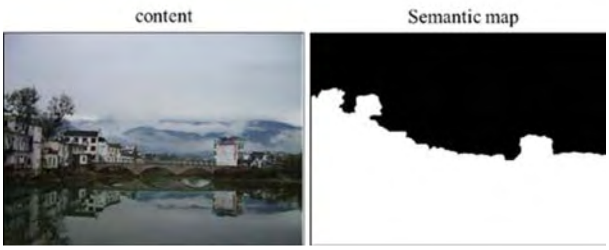

Figure 1. Example of the content and the semantic map.

2.3 CycleGAN

CycleGAN [19] was first introduced in 2017 using a powerful generative modeling framework, generative adversarial network (Goodfellow et al., 2014), for image translations. It learns a two-way mapping i.e. from domain A to domain B and vice-versa using two GANs constrained with a cycle-consistency loss term. The model can learn an image-to-image translation (i.e. pix2pix) without input-output pairs. It works well on tasks that involve color or texture changes, like day-to-night photo translations, or photo-to-painting tasks. Here we gave a season transfer example in Figure 2. However, the model does not work well when the test image is rather different from the images on which the model is trained.

Since all of the three methods are good methods of style transfer, therefore we take a typical network from each method used for all our experiments.

3. Experiments

In this section, we present the experimental details. Section 3.2 we present the experiment from photo to Oriental paintings by CycleGAN. Section 3.2 we experimentally

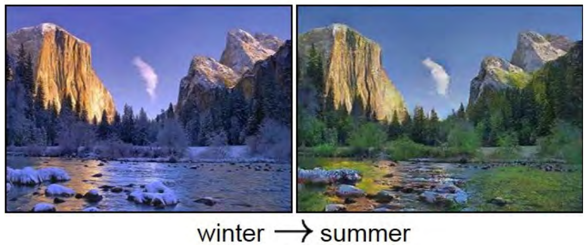

Figure 2. Example of winter to summer by CycleGAN.

compare the semantic style transfer network and neural-style-transfer (Gatys et al.) about Oriental paintings images.

3.1 CycleGAN

Dataset We used the Oriental Paintings dataset contains 1000 content images and 100 style images, collected from the website. The style images include diverse types of Oriental paintings. Some typical examples are presented below (Figure 3). The content images including diverse types of landscape photographs.

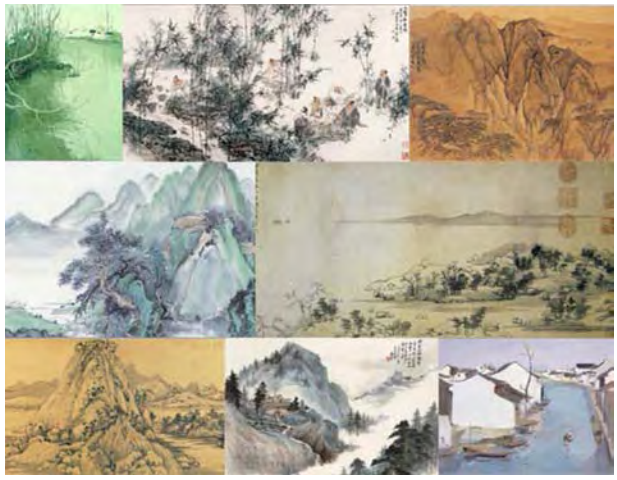

Figure 3. Sampled style images from the Oriental Paintings dataset.

Data Preprocessing For training, we first stochastically flipped the original images across the vertical axis i.e. horizontally following the center-cropping of these input images to 2562 resolution. Finally, the images were normalized with a mean and standard deviation of 0:5 each for all the channels. During training, the images were sampled randomly for stochastically training the CycleGAN.

Neural Network This network contains similar to (Zhu et al., 2017) two stride-2 convolutions, several residual blocks [16], and two 1/2-stride convolutions.

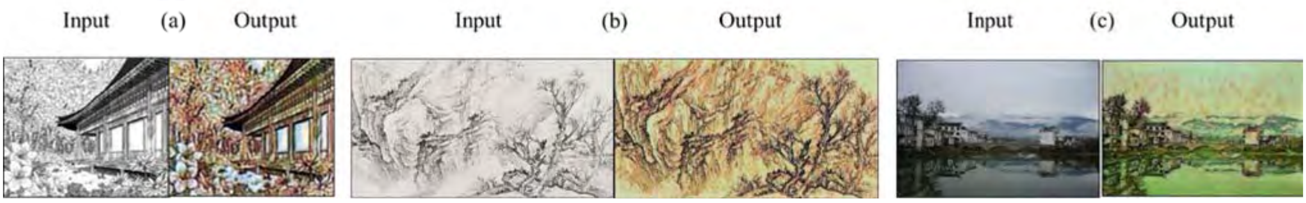

Figure 4. Style transfer of different image samples (left to right). Left: input of original image. Right: output of artist style transfer of Oriental paintings style by the CycleGAN. (a) Landscape sketch (b) Chinese landscape painting (c) Scenic photo.

Figure 5. Samples of transferring the photograph to the style of Oriental paintings (from left to right): style, content, Gatys et al., semantic map.

Figure 6. Samples of transferring the paintings to the style of Oriental paintings (from left to right): style, content, Gatys et al., semantic map.

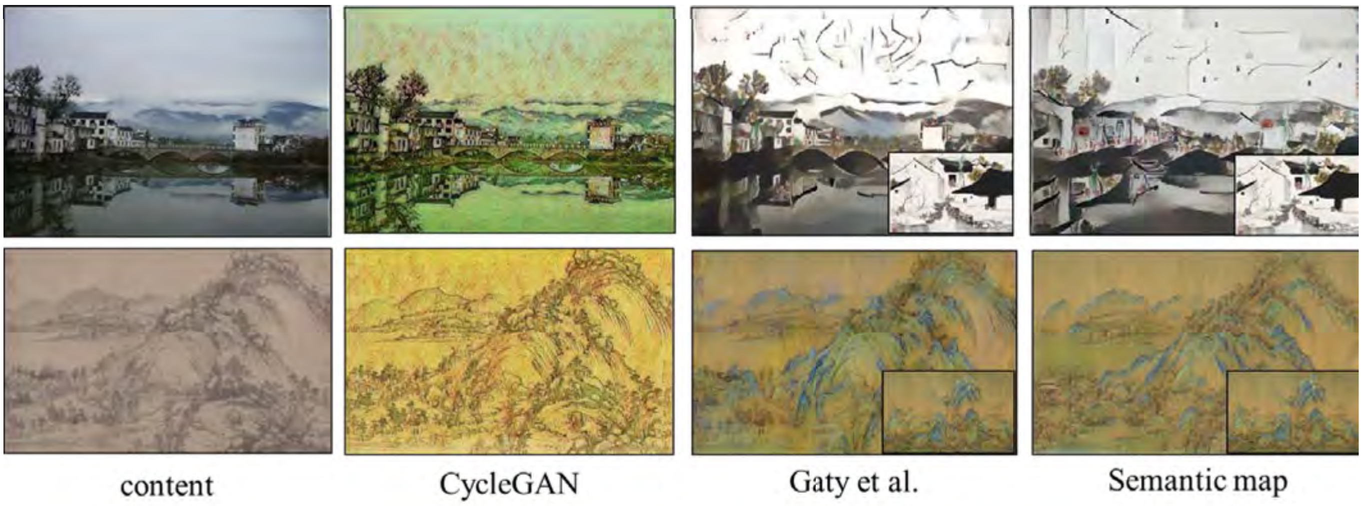

Figure 7. We compare CycleGAN with Gatys et al. and Semantic map. Left to right: content images, results from CycleGAN using the images from an entire set of the Oriental Paintings, results from Gatys et al. and Semantic map using single image as a style image.

Training In all the experiments a batch size of 4 was used for optimizing the networks with stochastic gradient descent. Specifically, the networks were trained with Adam (Kingma and Ba, 2014) optimizer with a constant learning rate of 0:0002 throughout training. Adam's hyper-parameter configurations β1 and β2 were tuned to 0:5 and 0:999, respectively. We trained the network for 12000 iterations and the average time taken is nearly 3 hours on a single NVIDIA (TITAN X) GPU machine.

Result Figure 4 (a) shows that conditioned on sketched Boundaries, the CycleGAN performs reasonably good quality in terms of image colorization. (b) shows that for the Chinese landscape painting, CycleGAN just colored the painting, without changing the content of the painting. (c) shows that CycleGAN performs reasonably good quality artist style transfer from scenic photo to paintings.

3.2 Effect compare

We experimentally compare the semantic style transfer network and neural-style-transfer (Gatys et al.) about Oriental paintings images. We did not present the experimental details about neural-style-transfer (Gatys et al.), only show the semantic style transfer network.

We chose the GLStyleNet [18] as an example of semantic style transfer network for all our experiments. The network not only flexible to adjust the tradeoff between content and style but also controllable between global and local style loss.

Training Details we download pre-trained vgg19 model.

We use L-BFGS to optimize the total loss. We trained the network for 400 iterations and the average time taken is nearly 6 hours on a single NVIDIA (TITAN X) GPU machine.

Result As shown in Figure 5, the method of semantic style transfer can retain local details as much as possible while also performs well on global features such as colors, which results in exquisite painting work. And its artistic style is captured better than the method proposed by Gatys et al. [2]. As shown in Figure 6, the method proposed by Gatys et al. get very rough results in more details. While the method of semantic style transfer uses a more elaborate semantic map to obtain good detail performance.

Compare We compare the three methods in Figure 7. Gatys et al. and Semantic map both use the single image as a style image, recombine the image content and style images to generate a new image. Note that unlike the two methods, CycleGAN learns to mimic the style of an entire set of the Oriental Paintings, rather than transferring the style of a single selected piece of art. CycleGAN performs reasonably good quality artist style transfer from scenic photo to paintings. However, CycleGAN does not performs good quality for the Chinese landscape painting. CycleGAN just colored the painting.

4. Discussion

In this paper, we compared three methods of style transfer. We take a typical network from each method in our experiments. From our experiments, we showed that the semantic map method can generate stylized Oriental paintings images qualified as more attractive in both visual and aesthetic assessments. While, CycleGAN learns to mimic the style of an entire set of the Oriental Paintings, rather than transferring the style of a single selected piece of art.

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