High-Resolution Network for Photorealistic Style Transfer

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Abstract

Photorealistic style transfer aims to transfer the style of one image to another, but preserves the original structure and detail outline of the content image, which makes the content image still look like a real shot after the style transfer. Although some realistic image styling methods have been proposed, these methods are vulnerable to lose the details of the content image and produce some irregular distortion structures. In this paper, we use a high-resolution network as the image generation network. Compared to other methods, which reduce the resolution and then restore the high resolution, our generation network maintains high resolution throughout the process. By connecting high-resolution subnets to low-resolution subnets in parallel and repeatedly multi-scale fusion, high-resolution subnets can continuously receive information from low-resolution subnets. This allows our network to discard less information contained in the image, so the generated images may have a more elaborate structure and less distortion, which is crucial to the visual quality. We conducted extensive experiments and compared the results with existing methods. The experimental results show that our model is effective and produces better results than existing methods for photorealistic image stylization. Our source code with PyTorch framework will be publicly available at https://github.com/limingcv/Photorealistic-Style-Transfer.

Keywords: Photorealistic style transfer, high-resolution network, photorealism.

1. Introduction

The main purpose of photorealistic image stylization (also known as color style transfer) is to transfer the style of color distributions Jing et al. (2017). Given a reference style, an input image can be transferred to make it look like it is in different lighting, time of day or weather, or it has been decorated with art with different intents. A successful stylization should keep the semantic content of the input image and the output image should look like a real photo made by the camera.

Conventional realistic stylized methods are usually based on tonal matching or color matching Reinhard et al. (2001); Pitie et al. (2005); Sunkavalli et al. (2010); Bae et al. (2006), but unfortunately these methods can only be used in special scenes, or the images after stylization look not real. Recently, Gatys et al. (2015, 2016) show that the gram matrix in feature map of convolution neural nets (CNN) can represent the style of an image and propose the neural style transfer algorithm for image stylization. Although the method has an amazing performance in the transfer of artistic image styles, the application to
photorealistic style transfer often results in generated images with less semantic information and distortions in the image than the content image as shown in Fig. 1(c).

Since CNN may lose some low-level information contained in the image during the downsampling process, some unattractive distortion structures and irregular artifacts usually exist in the stylized results. In order to maintain the consistency of the fine structure during the stylization process, Li et al. (2017a) suggests adding additional constraints on low-level features in pixel space. An additional Laplace loss (defined as the square Euclidean distance between the Laplacian filter response of the content image and the stylized result) is introduced. Although Li’s algorithm maintains fine structure and details in the stylization process with good performance, it still lacks considerations such as semantics, depth, and changes in brush strokes, as shown in Fig. 1(d).

Some style transfer algorithms also apply a spatial invariant transfer function to process the image, but these algorithms can deal with simple styles transfer such as global color shift and tone curves only. For example, to convert the input and style images to a decorrelated color space, Reinhard et al. (2001) proposed to match the mean and standard deviation between the input and style images. Pitie et al. (2005) also proposed an algorithm to transfer a full 3D color histogram based on a series of 1D histograms. These methods however have limited ability to match complex styles (c.f. Section 4) Luan et al. (2017) proposed a two-stage optimization procedure to first stylise a given photo with non-photorealistic style transfer algorithm and then penalise image distortions by adding a photorealism regularization. However, it usually produces inconsistent styles with obvious artifacts and is computationally expensive.
To address these issues, we propose in this paper a High-Resolution Network for Photorealistic Style Transfer. Inspired by the network proposed by Johnson et al. (2016), our solution has a generation network to generate the output image, and a pre-trained network to calculate the content loss and style loss, but the architecture of our generation network is different from the network in Johnson et al. (2016). To make the natural image photorealistic style transfer method successful with a more elaborate structure and less distortion, we use the high-resolution network as the generation network. In addition, we use VGG19 as the loss network to calculate the losses instead of the VGG16, because we found in our studies that the pre-trained VGG19 is better than the pre-trained VGG16.

The main contributions of this paper are three-fold: First, we propose a high-resolution network as the generation network to transfer the style with a finer structure and less distortion. Second, we implement the photorealistic style transfer successfully using traditional natural image style transfer algorithm, which provides a new choice for photorealistic style transfer. Last, we conduct extensive experiments to evaluate our proposal. Compared with Luan et al. (2017), our algorithm outperforms existing work in terms of a more elaborate structure, less distortion and a faster rate (c.f. Section 4).

The rest of this paper is organized as follows: Section 2 reviews the state-of-the-art efforts on style transfer. Section 3 presents our methodology. Section 4 evaluates our proposal and makes a comparison with existing solutions. Section 5 concludes the work and highlights some potential directions.

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1. All content images and style images except Fig. 4 and Appendix A can be found in Luan et al. (2017). The experimental results of other methods are also from Luan et al. (2017).
Figure 3: Overview of our network. The output image is generated by the high-resolution generation network, and then input into the pre-trained VGG to calculate the content loss and style loss. The parameters in the generation network are updated by back propagation of the total loss to make the output image better.

2. Related Work

2.1. Neural Style Transfer

Gatys et al. (2016) proposed a neural style transfer algorithm for artistic stylization. The core idea of the algorithm is to extract features and calculate content loss and style loss through a pre-trained network. Many followup research efforts such as Johnson et al. (2016); Li and Wand (2016); Ulyanov et al. (2016); Li et al. (2017b); Chen et al. (2017); Dumoulin et al. (2017); Ghiasi et al. (2017); Huang and Belongie (2017); Li et al. (2017c); Liao et al. (2017) have been devoted to further improving their stylized performance and speed. However, these methods are unable to maintain photorealism (c.f. 1(c)). Some researchers also proposed post-processing techniques to improve these results by matching the gradient between the input and output photos Li et al. (2017a); Mechrez et al. (2017).

Johnson et al. (2016) and Ulyanov et al. (2016) proposed the fast style transfer algorithms. These two methods share a similar idea, that is, train a generation network to generate the output image, and then put the output image, style image and content image into a pre-trained VGG to calculate the loss, and finally update the parameters of the generated network through back propagation. As the number of iterations increases, the output image becomes better.

2.2. High-Resolution Network

Our generation network is inspired by Sun et al. (2019), who proposed the high-resolution network for pose estimation and refreshed the record of the COCO pose estimation data set. Most networks have the high-to-low and low-to-high processes.

The high-to-low process aims to produce lower resolutions and higher channel counts, while the low-to-high process is designed to produce high-resolution representations and reduce the resolution of the feature maps. High-resolution network is designed to maintain high resolution representations through the whole process and continuously receive information from low-resolution networks. The high-resolution network has two benefits in
Figure 4: The influence of different content weights and style weights on the output image. $C_w$ is the content weight and $C_s$ is always 1. When the content weight is small, the output image tends to contain only a small amount of semantic information and precise structure of the content image. Conversely, if the style weight is much smaller than the content weight, the output image contains almost no color distribution in the style image.

comparison to other networks. (i) The high-resolution network connects both high and low resolution subnets in parallel, rather than connecting in series like most existing networks. (ii) Perform repeated multi-scale fusion with the help of low resolution representations of the same depth and similar levels to enhance high resolution representation.

### 2.3. Recent Work in Photorealistic Style Transfer

Closest to our work is the methods of Luan et al. (2017) and Li et al. (2018), but our approach is different from their methods. Luan et al. (2017) proposed a two-stage optimization program to first style a given photo using a non-photorealistic style transfer algorithm Champandard (2016), and then penalize image distortion by adding regularization to the photo to achieve good results. Li et al. (2018) also proposed a two-step solutions (i.e., the stylisation step and smoothing step) to address the efficiency issue. Since the proposed method uses the pixel affinity of the content, it may cause the style transfer to exist only in part of the area. Our approach is to update the network parameters by back propagation to make the generated image look better. For high resolutions images, our method is more efficient, because we only need to train a small number of times to achieve good results (usually 200 training steps for the 500×500 content images).
3. Photorealistic Style Transfer

3.1. Hi-Res Generation Network

*High-Resolution Generation Network*  Our model basically follows the model used by Johnson et al. (2016) for neural style transfer. There is a generation network and a loss network in the model. The generation network generates the output image, which is placed in the loss network (VGG19), and then updates the parameters of the generated network by calculating the content loss and the style loss. Our image generation network roughly follows the architectural guidelines proposed by Radford et al. (2015). We use strided convolutions for in-network downsampling without any pooling layers. The overall structure of our model is shown in Fig. 3, and the high-resolution generation network is shown in Fig. 2. For high-resolution generation network, in the same resolution propagation process, we used the bottleneck residual. All the convolutional layers use $3 \times 3$ kernels, and the mode selected for upsampling is bilinear. Furthermore, we use all zero padding to ensure the same resolution (we have tried other padding methods like reflection padding, but the effect is not good.) When it comes to the fusion between different feature maps, we concatenate these feature maps received like the inception module. This allows high-resolution subnets to have both high-resolution feature map information and low-resolution feature map information.

*Inputs and Outputs*  For photorealistic style transfer the input image and output image are both color images of shape $3 \times 500 \times 500$ by resizing, but all style images retain their original resolution. The resolution of the content image must be divisible by four, as shown in Fig. 2, we will obtain some feature maps with a resolution of one quarter of the input image by downsampling. The style image and the content image resolution can be the same, but this should be based on the principle that not changes the resolution of the style image. Once we change the resolution of the style image, the style distribution in the style image may not be transferred to the output image, which causes only a portion of the output image to contain the style in the style image.

*Upsampling and Downsampling*  All downsampling layers are convolution layers with a convolution kernel of $3 \times 3$. We use all zero padding instead of other padding methods like reflection padding, which make our output image have richer semantic information. Similar to Radford et al. (2015), we do not use any pooling layers like max-pool or mean-pool. The pattern used by our upsampling layer is bilinear interpolation, because in our studies, the results of using bilinear interpolation are slightly better than using nearest neighbor interpolation or cubic interpolation.

3.2. Perceptual Loss Functions

We think the content image and the output image should have the similar feature representations computed by the loss network VGG, which means we want the content image and the output image have the same feature map extracted by VGG, rather than encouraging the pixels of the content image exactly match the pixels of the output image. The total loss consists of the content loss and the style loss. The content loss is the (squared, normalized) Euclidean distance between feature maps:
\[ \ell^{\phi,j}_{\text{content}}(y, \hat{y}) = \frac{1}{C_j H_j W_j} \| \phi_j(\hat{y}) - \phi_j(y) \|^2 \]  

(1)

\( \hat{y} \) is the output image and \( y \) is the content image. When the input image is \( x \), \( \phi_j(x) \) is the activations of the \( j^{th} \) layer of loss network \( \phi \). If \( j \) is a convolutional layer, then \( \phi_j(x) \) is a feature map with the shape of \( C_j \times H_j \times W_j \). So the Gram matrix \( G_j^\phi(x) \) is the \( C_j \times C_j \) matrix whose elements are given by:

\[ G_j^\phi(x)_{c,\hat{c}} = \frac{1}{C_j H_j W_j} \sum_{h=1}^{H_j} \sum_{w=1}^{W_j} \phi_j(x)_{h,w,c} \phi_j(x)_{h,w,\hat{c}} \]  

(2)

If each point on the grid is interpreted as giving \( C_j \) dimensional features \( \phi_j(x) \), then \( G_j^\phi(x) \) is proportional to the non-center covariance of the dimensional features, and each grid position can be regarded as an independent sample. The information about which features tend to be activated together is thus captured. We can compute the Gram matrix efficiently by reshaping \( \phi_j(x) \) into a matrix \( \psi \) with the shape of \( C_j \times H_j \times W_j \), which means \( G_j^\phi(x) = \psi \psi^T / C_j H_j W_j \). Then, the style loss is defined as the squared Frobenius norm of the difference between the Gram matrices of the output and content images:

\[ \ell^{\phi,j}_{\text{style}}(y, \hat{y}) = \| G_j^\phi(y) - G_j^\phi(\hat{y}) \|^2 \]  

(3)

Given style image \( y_s \) and content image \( y_c \), the layers \( j \) and \( J \) at which to perform feature and style reconstruction, \( \lambda_c \) is the content weight, \( \lambda_s \) is the style weight and \( \lambda_{TV} \) is the total variation regularizer, an image \( \hat{y} \) is generated by solving the problem:

\[ \hat{y} = \arg \min_y \lambda_c \ell^{\phi,j}_{\text{content}}(y, y_c) + \lambda_s \ell^{\phi,J}_{\text{style}}(y, y_s) + \lambda_{TV} \ell_{TV}(y) \]  

(4)

### 3.3. Implementation Details

This section describes the implementation details of our approach. We resize all the images to 500×500 and then use the pre-trained VGG19 provided by PyTorch as the feature extractor to calculate content loss and style loss. We choose conv4_2 as the content representation, conv1_1(weight:0.1), conv2_1(weight:0.2), conv3_1(weight:0.4), conv4_1(weight:0.8) and conv5_1(weight:1.6) as the style representation. We do not use dropout, but for some situations (like the resolution of content image varies greatly with the resolution of style image), weight decay is a good way to get good results. The total style loss is equal to the sum of each layer’s style loss multiplied by its weight. The combination of different content pictures and style pictures has different style weight and content weight, but in general, we achieve good results with content weights equal to \([50, 100]\), and style weights equal to \([1, 10]\). For all residual bottleneck layers, we first use 3×3 convolution to make the number of channels of the feature map a quarter of the input feature map, and finally use 1×1 convolution to restore the number of channels. We use Adam Kingma and Ba (2014) with a learning rate of 1×10^{-3}. The effect of content weight and style weight is illustrated in Fig. 4.
4. Experiments

4.1. Experimental Setup

We compare the proposed algorithm with two types of stylized algorithms: realism and artistry. Photo-realistic style algorithms evaluated include Reinhard et al. (2001); Pitie et al. (2005); Luan et al. (2017). Reinhard et al. (2001) and Pitie et al. (2005) represents a classic technique based on color statistics matching, and Luan et al. (2017) is based on the neural style transfer algorithm Johnson et al. (2016). On the other hand, the set of artistic style algorithms evaluated includes Gatys et al. (2016) and Li and Wand (2016). They all use deep networks to realize the fusion of style images and content images. In the experiments, we extracted the contour information of the image and compare the effects (e.g., finer structure and less distortion) of our solution with above mentioned solutions. We also compared the time of different solutions using in the training.

We also conducted two empirical studies to compare the visual effects. We invited students from different grades and different majors to choose the most successful images of style transfer, the pictures with richer semantic information and the best visual images. In order to ensure the accuracy and credibility of the results, the ratio of male to female participants is about 1:1. Their majors include art, science, engineering, management, etc. In addition, to make the subjects in the study representative and diverse, nearly one-third subjects are students from universities in other cities.

4.2. Results

The experimental results show that our output images have a contour closer to the content image, indicating that our results have more semantic information. The speed comparison shows that our algorithm runs faster than Luan et al. (2017) and the empirical study shows that more people regard our results as more faithful. Detailed Comparison are illustrated as follows:

**Effect Comparison** We compare our approach to Gatys et al. (2016)(Neural style transfer) and Li and Wand (2016) (CNNMRF). As shown in Fig. 5, both of these techniques produce results similar to the distortion of the painting, which are carried out in the context of the shift in photographic style. In several cases, the neural style algorithm is also affected by the spillover effect, CNNMRF often generates partial style transfers, ignoring important parts of the style image. In contrast, our images are generated by a high-resolution generation network that prevents these artifacts from happening, furthermore, our results look more like real-life photos. Compared to Luan’s proposed method, our output image has a more uniform color distribution, which makes our images have more realistic semantic information (e.g. Closet color in the upper left corner in Fig. 5(e).)

We also compare our approach to global style delivery methods that do not distort the image Reinhard et al. (2001) and Pitie et al. (2005). As shown in Fig. 6, both their techniques apply a global color map to match the color statistics between the input image and the style image, which limits the loyalty of the results when transmitting a color transform that requires spatial variation. Luan et al. (2017) achieves a good stylized effect at first glance, however, careful observation revealed that the resulting photograph contained significant artifacts, e.g. the irregular shape of petals and white tent. Several semantically
Figure 5: Comparison of our method against Neural Style, CNNMRF and Luan et al. (2017). Both neural transfer and CNNMRF produce image distortion in the output image. The neural transfer also completely ignores the semantic information of content image. Compared to Luan, our method has a more elaborate structure and a more realistic color distribution.
Figure 6: Our approach provides greater flexibility in delivering spatially varying color variations and produces better results than Reinhard et al. (2001) and Pitie et al. (2005). Compared to Luan et al. (2017), our output image has a more uniform color distribution and better image detail (e.g., the white tent).
Table 1: Run-time comparison. We calculated the running time of these algorithms at different resolutions (in seconds) with a GTX 1060 GPU, cuda 9.0 and cuDNN Chetlur et al. (2014).

|                | Gatys et al. (2016) | Johnson et al. (2016) | Luan et al. (2017) | Ours            |
|----------------|---------------------|-----------------------|--------------------|-----------------|
| **13.14**      | 83.74(128×128)      | 199.01(256×128)       | 59.72(128×128)     |                 |
| **39.68**      | 148.99(256×256)     | 466.3(512×256)        | 110.91(256×256)    |                 |
| **126.84**     | 434.18(512×512)     | 952.05(768×384)       | 380.66(512×512)    |                 |

Table 2: User preference score comparison with Reinhard et al. (2001) and Pitie et al. (2005):

|                                | Reinhard et al. (2001) | Pitie et al. (2005) | Ours  |
|--------------------------------|------------------------|---------------------|-------|
| More style information         | 46.83%                 | 13.88%              | 39.29%|
| More semantic information      | 20.42%                 | 26.31%              | 53.27%|
| Better visual effect           | 17.27%                 | 19.92%              | 62.81%|

similar regions are stylized inconsistently. In contrast, our approach is more capable of retaining semantic information in content images while successfully transferring styles.

**Speed Comparison** As can be seen from Table 1, our method is much faster than Johnson et al. (2016) and Luan et al. (2017). The numbers in parentheses represent the resolution of the style image and the content image. Since Luan et al. (2017) method is special, we did not reproduce their work, but estimated the computing power of different GPUs used. The estimation and comparison of computing power between different GPUs comes from the official website of NVIDIA. Compared with the method proposed by Gatys et al. (2016), although our method requires more time to train once, the number of trainings required by their method to achieve good results is much greater than the number of trainings required by our method, and their approach is prone to distortion as shown in Fig. 5(c) and 5(i).

**Visual Comparison** Three evaluation indicators, including more style information, rich semantic information and better visual effects are used in our empirical studies. The result

Table 3: User preference score comparison with Gatys et al. (2016)(Neural Style), Li and Wand (2016)(CNNMRF) and Luan et al. (2017):

|                                | Neural Style | CNNMRF | Luan et al. (2017) | Ours  |
|--------------------------------|--------------|--------|--------------------|-------|
| More style information         | 23.65%       | 4.30%  | 34.41%             | 38.04%|
| More semantic information      | 11.83%       | 8.61%  | 25.80%             | 53.76%|
| Better visual effect           | 17.20%       | 3.23%  | 29.03%             | 50.54%|
of first study is shown in Table 2. Compared with these classic realistic stylized methods Reinhard et al. (2001) and Pitie et al. (2005), although our method scores slightly lower in style transfer, the scores of semantic information and visual effects are greater than the sum of other algorithms. The second study results are shown in Table 3. We compare the results with Neural Style, CNNMRF and Luan et al. (2017), and it turns out that our stylized images have more style information, more semantic information and better visual effect than existing methods. These two studies show that our method can produce better stylized images than existing methods. In particular, our method is slightly inferior to Reinhard et al. (2001) in terms of more style information, but our methods are better than these methods in terms of more semantic information and better visual effects.

5. Conclusion

We designed a high-resolution generation network as the model generation network. By connecting multiple subnets in parallel and repeating multi-scale fusion, the neural style transfer algorithm using the high-resolution network achieves good results in photorealistic style transfer with a finer structure and less distortion of images. We conducted extensive experiments and empirical studies to evaluate the proposal. The experimental results show that compared with existing methods, the stylized output image by our algorithm has better visual effects and faster generation speed.

Although our algorithm can achieve better results more quickly than existing methods, it is still unable to transfer photorealistic style in real-time. We plan to use the high-resolution generation network trained on the big data set as the loss network instead of the generation network. Due to the characteristics of the high-resolution network, it may be able to extract the feature information of the image well compared to the pre-trained VGG network. In addition, although our method can perform a good image style transfer on the whole picture, we cannot transfer the style of a specific thing in the image. In the future, we plan to use the instance segmentation to realize the instance image style transfer.

Acknowledgments

We thank Leon Gatys, Fujun Luan, Yijun Li, Ke Sun, Justin Johnson for their great work as well as the reviewers for their valuable discussions. This work was supported in part by the Key Research and Development Program of Hainan Province under grant No. ZDYF2017010, the National Natural Science Foundation of China under grant No. 61562019, 61379047, 60903052, and grants from State Key Laboratory of Marine Resource Utilization in South China Sea and Key Laboratory of Big Data and Smart Services of Hainan Province.

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Appendix A. More Results

More results of our approach can be referred to Figure 7. We also compare the contour of resulting images produced by different solutions through image graying, as shown in Figure 8. By using the sobel operator to extract the contour of the resulting images and comparing them with those of the content images, we can observe that the images after stylization based on our approach preserve more semantic information and have a finer structure than existing solutions.
Figure 7: More results
Figure 8: Grayscale and contour images