Arbitrary Style Transfer via Multi-Adaptation Network

Yingying Deng, Fan Tang, Weiming Dong Member, IEEE, Sun Wen, Feiyue Huang, Changsheng Xu, Fellow, IEEE

Abstract—Arbitrary style transfer is a significant topic with both research value and application prospect. Given a content image and a referenced style painting, a desired style transfer would render the content image with the color tone and vivid stroke patterns of the style painting while synchronously maintain the detailed content structure information. Commonly, style transfer approaches would learn content and style representations of the content and style references first and then generate the stylized images guided by these representations. In this paper, we propose the multi-adaption network which involves two Self-Adaptation (SA) modules and one Co-Adaptation (CA) module: SA modules adaptively disentangles the content and style representations, i.e., content SA module uses the position-wise self-attention to enhance content representation and style SA module uses channel-wise self-attention to enhance style representation; CA module rearranges the distribution of style representation according to content representation distribution by calculating the local similarity between the disentangled content and style features in a non-local fashion. Moreover, a new disentanglement loss function enables our network to extract main style patterns to adapt to various content images and extract exact content features to adapt to various style images. Various qualitative and quantitative experiments demonstrate that the proposed multi-adaption network leads to better results than the state-of-the-art style transfer methods.

Index Terms—Arbitrary style transfer; Feature disentanglement; Adaptation

I. INTRODUCTION

Artistic style transfer is a significant technique which focuses on rendering natural images with artistic style patterns and maintaining the content structure of natural images at the same time. Traditional style transfer methods are mainly based on texture synthesis or physical stimulation [1], [2] to render photographic images by utilizing different painting styles. However, these methods are usually time-consuming and cannot produce high-quality transfer results. In recent years, researchers have applied convolutional neural networks (CNN) to perform image translation and stylization [3], [4]. Gatys et al. [4] innovatively used deep features extracted from VGG16 to represent image content structure and calculate the correlation of activation maps to obtain image style patterns. However, this optimization-based method is also time-consuming and hard to make a trade-off between the content structure and style patterns in the generated images. Based on [4], many works either speed up the transfer procedure or promote the generation quality [4]–[10]. Johnson et al. [5] used feed-forward neural networks to achieve the purpose of real-time style rendering. Gatys et al. [11] improved the basic model of [4] to get higher quality results and broaden the applications. However, these methods are difficult to generate stylized results in real time by using arbitrary style image as a reference, which limits the application prospect.

To further expand the application of style transfer, many works focus on arbitrary style transfer methods [12]–[19]. Some works [12], [20] align the second order statistics of style image to content image. Huang et al. [20] proposed adaptive instance normalization (AdaIn) to adjust content image according mean and variance of style images. However, over-simplifying the style transfer process makes the generated
quality disappointing. Li et al. [12] adjusted the covariance of the content image through whitening and coloring transformation (WCT) operation, which based on a pre-trained encoder-decoder structure. The holistic transformation may bring some unconstrained style patterns and structure distortion. Patch-swap-based methods [17], [21] aim to transfer style image patches to content image according to the similarity between patches pairs. However, when the distributions of content and style structure vary greatly, little style patterns are transferred to the content image through style-swap [21]. Yao et al. [17] improved the style-swap [21] method by adding multi-stroke control and self-attention mechanism. Although self-attention is used to make the main structure of the content image clear, the non-main structures will be damaged and the transferred style patterns in the generated image is not obvious. Inspired by self-attention mechanism, Park et al. [15] proposed style-attention to match the style features onto the content features, but may encounter semantic structures of content image distorting problem. Moreover, most style transfer methods use a common encoder to extract features of content images and style images, which neglect the domain-specific features contributing to better generation.

In recent years, some researchers [3], [22]–[29] use Generative Adversarial Networks (GAN) for high-quality image-to-image translation. The GAN-based methods can generate high-quality artistic works that can be taken as real. The style and content representation is essential for the translation model. Plenty of works [23], [24], [26], [27] put their focus on the disentanglement of style and content for allowing models to be aware of isolated factors of deep features. Although the image-to-image translation can achieve the multi-modal style-guided translation results, it is hard to be adapted to arbitrary style transfer because of its limitation in unseen domain.

To enhance the generation effect of arbitrary style transfer methods aforementioned, we propose a flexible and efficient arbitrary style transfer model with disentanglement mechanism for preserving the detailed structures of the content images, while transferring rich style patterns of referenced paintings to generated results. As shown in Figure 1 state-of-the-art methods can render the referenced color tone and style into the content image. However, the content structures (outline of the houses) and stroke patterns are not well preserved and transferred. In this work, we propose multi-adaptation network which involves two Self-Adaptation (SA) modules and one Co-Adaptation (CA) module. The SA module uses the position-wise self-attention to enhance content representation and channel-wise self-attention to enhance style representation, which adaptively disentangles the content and style representation. Meanwhile, the CA module adjusts the style distribution to adapt to content distribution. Through interaction between SA and CA, our model can learn effective content and style features and rearrange the style features according to content features. Then, we merge the rearranged style features and content features to obtain the generated results. Through the self-adaptation and co-adaptation procedure, our method considers both the global information in content and style image and local similarity between image patches. Moreover, we introduce a novel disentanglement loss for style and content disentanglement. When generating a series of stylized results using common content image and different style images, the content disentanglement loss makes the content features extracted from stylized results similar. When generating a series of stylized results using common style image and different content images, the style disentanglement loss makes the style features extracted from stylized results similar. The disentanglement loss makes the network extract main style patterns to adapt to various content images, and extract exact content features to adapt to various style images. In summary, our main contributions are:

- A flexible and efficient multi-adaptation arbitrary style transfer model involving two SA and one CA modules.
- A novel disentanglement loss function for style and content disentanglement to extract well-directed style and content information.
- Various experiments illustrate that our method can preserve the detailed structures of the content images, and transfer rich style patterns of reference paintings to the generated results. Furthermore, we analyze the influence of different convolutional receptive field sizes on CA module when calculating the local similarity between disentangled content and style features.

II. RELATED WORK

a) Style Transfer: Since Gatys et al. [4] proposed the first style transfer method using CNN, many works are devoted to promoting the transfer efficiency and generation effects. Some works [5], [6], [30] put forward real-time feed-forward style transfer networks, which can only transfer one kind of style through training an independent network. To obtain wide range of applications, arbitrary style transfer becomes a major research topic. Chen et al. [21] firstly swapped the style images patch onto content images based on patch similarity, and achieved fast style transfer for arbitrary style images. Huang et al. [20] proposed adaptive instance normalization (AdaIn) to adjust the mean and variance of content images to style images in a holistic fashion. Using whitening and coloring transform (WCT), Li et al. [12] aligned the covariance of style images and content images, and transferred multi-level style patterns to content images to obtain better-stylized results. To combined the local and global style patterns to stylized results, Avatar-Net [19] applied style decorator to guarantee semantically aligned and holistically matching. Park et al. [15] proposed a style-attention network to match the style features onto the content features to achieve attractive results with obvious style patterns. Yao et al. [17] achieved multi-stroke style results using self-attention mechanism.

However, the above arbitrary style transfer methods cannot well balance content structure preservation and style patterns rendering. The disadvantages of these methods can be observed in Section IV-B. Therefore, we aim to propose an arbitrary style transfer network which effectively transfers style patterns to content image while maintaining the detailed content structures.

b) Feature Disentanglement: In recent years, researches [3], [22]–[29] used generative adversarial networks (GAN) to achieve image-to-image translation, which can be
Yu et al. [27] disentangled the input to latent code through an distribution according to content distribution through the co-

Adaption module and get the generated features \( f_{cs} \). Finally, we generate the results \( I_{cs} \) through decoder. Moreover, The losses are calculated through a pre-trained VGG19. \( L_{content} \) measures the difference between \( I_{cs} \) and \( I_{c} \). \( L_{style} \) measures the difference between \( I_{cs} \) and \( I_{s} \). (b) The disentanglement loss. \( L_{dis-content} \) measures the content difference among stylized results, which are generated by using different content images and same content image. \( L_{dis-style} \) measures the style difference among stylized results, which are generated by using different content images and same style image. (c) Identity loss. \( L_{identity} \) measures the difference between \( I_{cs}(I_{s}|i) \) and \( I_{s}(I_{s}) \), where \( I_{cs}(I_{s}|i) \) is the stylized results using two same content(style) images.

III. METHODOLOGY

For the purpose of arbitrary style transfer, we propose a feed-forward network, which contains an encoder-decoder architecture and a multi-adaption module. The structure of our network is shown in Figure 2. We use a pre-trained VGG19 network as an encoder to extract deep features. Given a content image \( I_{c} \) and style image \( I_{s} \), we can extract corresponding feature maps \( f_{c}^{i} = \mathcal{E}(I_{c}) \) and \( f_{s}^{i} = \mathcal{E}(I_{s}), i \in \{1, ..., L\} \). However, the encoder is pre-trained using ImageNet dataset for classification tasks, which is not suitable enough for style transfer tasks. Meanwhile, due to the domain deviation between artistic paintings and photographic images, using a common encoder can only extract a few domain-specific features. Therefore, we put forward a multi-adaption module to disentangle style and content representation through the self-adaptation process, and then rearrange the disentangled style distribution according to content distribution through the co-adaptation process. Through multi-adaption module, we can get stylized features \( f_{cs} \). The detailed description of multi-adaption module is shown in Section III-A. The decoder is a mirrored version of the encoder, and we can obtain the generated result \( I_{cs} = D(f_{cs}) \). The model is trained by minimizing three types of loss functions described in Section III-B.

A. The Multi-Adaption Module

The multi-adaption module is shown in Figure 3 which is divided into three parts: Position-wise Content Self-Adaptation module, Channel-wise Style Self-Adaptation module, and Co-Adaptation module. We disentangle the content and style through two independent position-wise content self-adaptation module and channel-wise style self-adaptation module. Through content/style self-adapt-ation module, we can disentangle the corresponding content/style representation \( f_{c}(f_{s}) \) to \( f_{cs}(f_{ss}) \). Then the co-adaptation module rearranges style representation according to content representation, and generates stylized features \( f_{cs} \).

a) Position-wise Content Self-Adaptation Module: Preserving the semantic structure of the content image in the stylized result is important, so we introduce position attention module in [31] to adaptively capture long-range information in content features. Given a content feature map \( f_{c} \in \mathbb{R}^{C \times H \times W} \), \( f_{c} \) denotes the whitened content feature map which removes textural information related to style using whitening transform in [12]. We feed \( f_{c} \) to two convolution layers, and generate two new feature maps \( f_{c1} \) and \( f_{c2} \). Meanwhile, we feed \( f_{c} \) to another convolution layer to generate new feature map \( f_{cs} \). We reshape \( f_{c1}, f_{c2} \) and \( f_{cs} \) to \( \mathbb{R}^{C \times N} \), where \( N = H \times W \). Then, the content spatial attention map \( A_{c} \in \mathbb{R}^{N \times N} \) is formulated as:

\[
A_{c} = \text{SoftMax}(\hat{f}_{c1} \otimes \hat{f}_{c2}),
\]
where $\otimes$ represents matrix multiplication, $\hat{f}_{c1} \otimes \hat{f}_{c2}$ represents the position-wised multiplication between two feature maps $f_{c1}$ and $f_{c2}$. Then, we obtain the enhanced content feature map $f_c$ through a matrix multiplication and an element-wise addition:

$$f_{cc} = f_{c3} \otimes A^T_c + f_c. \quad (2)$$

b) Channel-wise Style Self-Adaptation Module: Learning style patterns (e.g. texture and strokes) of the style image is important for style transfer. Inspired by [4], the channel-wise inner product between the vectorized feature maps can represent style, so we introduce channel attention module in [31] to adaptively enhance the style patterns in style images. Different from the content self-adaptation module, the input style features do not need to be whitened. We feed the style feature map $f_s \in \mathbb{R}^{C \times H \times W}$ to two convolution layers, and generate two new feature maps $f_{s1}$ and $f_{s2}$. Meanwhile, we feed $f_s$ to another convolution layer to generate new feature map $f_{s3}$. We reshape $f_{s1}$, $f_{s2}$ and $f_{s3}$ to $\mathbb{R}^{C \times N}$, where $N = H \times W$. Then, the style spatial attention map $A_s \in \mathbb{R}^{C \times C}$ is formulated as:

$$A_s = SoftMax(f_{s1} \otimes f_{s2}^T), \quad (3)$$

where $f_{s1} \otimes f_{s2}^T$ represents the channel-wised multiplication between two feature maps $f_{s1}$ and $f_{s2}$. Then, we adjust the style feature map $f_s$ through a matrix multiplication and an element-wise addition:

$$f_{ss} = A^T_s \otimes f_{s3} + f_s. \quad (4)$$

c) Co-Adaptation Module: Through the self-adaptation module, we obtain the disentangled style features and content features. Then, we push forward the Co-Adaptation module to calculate the correlation between the disentangled features, and adaptively recombine them onto an output feature map. The generated results can not only retain the prominent content structure, but also adjust semantic content with the appropriate style patterns according to the correlation. The co-adaptation process is shown in Figure 3. Firstly, whitening the disentangled style feature map $f_{ss}$ and content feature map $f_{cc}$ to $\hat{f}_{ss}$ and $\hat{f}_{cc}$. Then, we feed $\hat{f}_{cc}$ and $\hat{f}_{ss}$ to two convolution layers to generate new feature map $\hat{f}_{cc1}$ and $\hat{f}_{ss2}$. Meanwhile, we feed feature map $f_{ss}$ to another convolution layer to generate new feature map $f_{ss3}$. We reshape $\hat{f}_{cc1}$, $\hat{f}_{ss2}$ and $f_{ss3}$ to $\mathbb{R}^{C \times N}$, where $N = H \times W$. Then, the correlation map $A_{cs} \in \mathbb{R}^{N \times N}$ is formulated as:

$$A_{cs} = SoftMax(\hat{f}_{cc1}^T \otimes \hat{f}_{ss2}), \quad (5)$$

where the value of $A_{cs}$ in position $(i, j)$ measures the correlation between the $i$-th position in content features and the $j$-th position in style features. Then, the rearranged style feature map $f_{rs}$ is mapped by:

$$f_{rs} = f_{ss3} \otimes A^T_{cs}. \quad (6)$$

Finally, the co-adaptation result is achieved by:

$$f_{cs} = f_{rs} + f_{cc}. \quad (7)$$

B. Loss Function

Our network contains three loss functions in training procedure.

a) Perceptual Loss: Similar to AdaIN [29], we use a pre-trained VGG19 to compute the content and style perceptual loss. The content perceptual loss $L_{content}$ is used to minimize the content difference between generated image and content image, where

$$L^i_{content} = \|\phi_i(I_{cs}) - \phi_i(I_c)\|_2. \quad (8)$$

The style perceptual loss $L_{style}$ is used to minimize the style difference between generated image and style image:

$$L^i_{style} = \|\mu_i(\phi_i(I_{cs})) - \mu_i(\phi_i(I_c))\|_2 + \|\sigma_i(\phi_i(I_{cs})) - \sigma_i(\phi_i(I_c))\|_2, \quad (9)$$

where $\phi_i(\cdot)$ denotes features extracted from $i$-th layer in a pre-trained VGG19, $\mu(\cdot)$ denotes the mean of features, and $\sigma(\cdot)$ denotes the variance of features.
b) Identity Loss: Inspired by [15], we introduce the identity loss to give a soft constraint on the mapping relation between style features and content features. The identity loss is formulated as:

\[
L_{\text{identity}} = \|I_c|_c - I_c\|^2 + \|I_s|_s - I_s\|^2, \tag{10}
\]

where \(I_c|_c\) is the generated results using one natural image as content image and style image simultaneously, \(I_s|_s\) is the generated results using one painting as content image and style image simultaneously.

c) Disentanglement Loss: To separate the representation of style and content, it is crucial to make the style features independent from the target content. I.e., when generating a series of stylized results using a common content image and different style images, the content disentanglement loss makes the content features extracted from stylized results similar. When generating a series of stylized results using a common style image and different content images, the style disentanglement loss makes the style features extracted from stylized results similar. Therefore, we propose a novel disentanglement loss as follows:

\[
\begin{align*}
L^c_{\text{dis-content}} &= \|\phi_i(I_c|s_1) - \phi_i(I_c|s_2)\|^2, \\
L^s_{\text{dis-style}} &= \|\mu(\phi_i(I_s|c_1)) - \mu(\phi_i(I_s|c_2))\|^2 + \|\sigma(\phi_i(I_s|c_1)) - \sigma(\phi_i(I_s|c_2))\|^2, \tag{11}
\end{align*}
\]

where \(I_c|s_1\) and \(I_c|s_2\) are generated results using common content image and different style images, \(I_s|c_1\) and \(I_s|c_2\) are generated results using common style image and different content images. The total loss function is formulated as:

\[
L = \lambda_c L^c_{\text{content}} + \lambda_{\text{dis-c}} L^c_{\text{dis-content}} + \lambda_{\text{id}} L_{\text{identity}} + \lambda_s \sum_{i=1}^{L} L^s_{\text{style}} + \lambda_{\text{dis-s}} \sum_{i=1}^{L} L^s_{\text{dis-style}}. \tag{12}
\]

In general, the loss functions constrain the global similarity between generated results and content/style images. The two SA modules calculate the long-range self-similarity of input features to disentangle the global content/style representation. The CA module rearranges the style distribution according to content distribution by calculating the local similarity between the disentangled content and style features in a non-local fashion. Therefore, our network can consider both the global content structure and local style patterns to generate fascinating results.

IV. EXPERIMENTS

A. Implementation Details

We use MS-COCO [32] as content dataset and WikiArt [33] as style dataset. In the training stage, both style and content images are randomly cropped to 256 × 256 pixels. In the testing stage, all image sizes are supported. We use \textit{conv1\_1}, \textit{conv2\_1}, \textit{conv3\_1}, and \textit{conv4\_1} layers in the encoder (pre-trained VGG19) to extract image features. The features of \textit{conv4\_1} layer are fed to multi-adaption module to generate the features \(f_c\). Furthermore, we use layer \textit{conv4\_1} to calculate the content perceptual and disentanglement loss, use \textit{conv1\_1}, \textit{conv2\_1}, \textit{conv3\_1}, and \textit{conv4\_1} layers to calculate the style perceptual and disentanglement loss. The convolution kernel sizes used in multi-adaption module are all set to 1 × 1. The weights \(\lambda_c\), \(\lambda_s\), \(\lambda_{\text{id}}\), \(\lambda_{\text{dis-c}}\), and \(\lambda_{\text{dis-s}}\) are set to 1, 5, 50, 1, and 1 respectively.

B. Comparison with Prior Work

a) Qualitative Evaluation: We compare our method with four state-of-the-art works: AdaIN [20], WCT [12], SANet [15] and AAMS [17]. The stylized results are shown in Figure 4. The AdaIN [20] adjusts the mean and variance of the content image to adapt to the style image globally. Although the content structures are well-preserved, it may result in inadequate textual patterns transferred in stylized images (see the 3rd and 7th rows in Figure 4). And the results may even appear different color distributions with style images (see the 1st, 4th, 5th and 8th rows in Figure 4). WCT [12] improves the style performance of AdaIN by adjusting the covariance of the content image through whitening and coloring transformation operation. However, WCT would introduce content distortion (see the 2nd, 4th, 6th, 7th and 8th rows). SANet [15] uses style-attention to match the style features to the content features, which can generate attractive stylized results with distinct style texture. But it may lead to repeat style patches in the generated results (see eyes in the 3rd row in Figure 4) and distort the content structures (see the 2nd, 4th and 8th rows in Figure 4). AAMS [17] is based on self-attention, hence the stylized images can preserve the structure of prominent part of the content images. However, the results are highly dependent on the attention map calculated by AAMS. It may generate unsatisfactory results that only maintain part content structures, and highly blur in the background (see the 2nd, 3rd, 4th, 5th and 8th rows in Figure 4).

Different from the above methods, in multi-adaption network, disentangled content and style features can well-represent domain-specific characteristic. Therefore, the results generated by our method can better preserve the content and style information. Moreover, through adaptive adjust the disentangled content and style features, our method can generate appealing results, which have both distinct content structures and rich style patterns. The content images can be rendered by corresponding style patterns according to their semantic structures (see the 1st row in Figure 4).

b) User Study: We conduct user studies to further compare the visual performance of ours and the SOAT methods aforementioned. We select 20 style images and 15 content images to generate 300 results for each method. Firstly, we show the participants each content-style pair. Then we show them two results, one is by our method and the other is randomly selected from one of the the SOAT methods. We ask the participants four questions: (1) which stylized result better preserves the content structures; (2) which stylized result better transfers the style patterns; (3) which stylized result has better visual quality overall; (4) when choosing the images in question (3), which factor is mainly considered: content, style, both or neither. We ask 30 participants to do 50 rounds of comparisons and get 1500 votes for each question. The statistical results are shown in Figure 5. From Figure 5(a), we can conclude that regardless of considering the aspects of content, style, or
Fig. 4. Comparison of stylized results with STOA methods. The first column shows style images, the second column shows content images. The rest columns are stylized results by our methods, AdaIn [20], WCT [12], SANet [15], AAMS [17].
The loss functions constrain the global similarity between generated results and content/style images. There are two factors that can change the perceptual field size.

Table I: Classification accuracy.

|          | AdaIn | WCT | SANet | AAMS | Ours |
|----------|-------|-----|-------|------|------|
| style(%) | 55.7  | 61.5| 65.2  | 57.9 | 62.9 |
| content(%) | 42.0 | 22.8| 29.1  | 33.0 | 34.6 |

Overall effect, our method obtains the majority votes. When choosing results with better visual performance overall, the participants are more impressionable to content than style.

Then we compare our method with each comparison method in the aspect of content, style, and overall separately in Figure 5b). The overall performance of our method is better than every comparison method. Compared with AdaIn [20], our results has clear advantages in style and comparable content preservation ability. Compared with WCT [12] and SANet [15], our results have clear advantages in content and has comparable style patterns. Compared with AAMS [17], our results both have clear advantages in content and style.

c) Quantitative Evaluation: To quantify the style transferring and content preservation ability of our method, we firstly introduce an artist classification model to evaluate how well the stylized results are rendered by every artist’s style. We select 5 artists each with 1000 paintings and divide them into training and testing sets in the ratio of 8:2. Then we fine-tune the pre-trained VGG19 model using the training set. We generate 1000 stylized images for each method. We feed the stylized images to artist classification model to calculate the accuracy. Secondly, we use a content classification model to quantify the content preservation effects of different methods. We randomly select 5 classes from the ImageNet dataset. Then we fine-tune the pre-trained VGG19 model using the training set of ImageNet. We use the corresponding validation set (5 classes, each class includes 50 content images) to generate 1000 stylized images for each method. We feed the stylized images to the content classification model to calculate the accuracy.

The classification results are shown in Table I. Both the style and content classification accuracy of our method are relatively high, which illustrates that our method can make a trade-off between content and style. Although the SANet gets the highest style classification accuracy, the content classification accuracy is too low to obtain attractive results. The content classification accuracy of AdaIn is high, but the style classification accuracy is low. In general, the content/style classification results of each method is consistent with user study results. The small statistical difference is because when participants choosing better content/style results, they may be influenced by the effect of generated results.

Fig. 7. Comparison of stylized results with different receptive field size. The meticulous structures of results in 3rd and 4th columns are not well-preserved compared with our results (see details in red box).

Table I: Classification accuracy.
C. Ablation Study

a) Verify the effect of disentanglement loss: We compare the generated results with and without disentanglement loss to verify the effect of disentanglement loss. As shown in Figure 6, compared to the stylized results without disentanglement loss, using disentanglement loss can generate results with the key style patterns of style image (purple feathers, Figure 6(a)) or more visible content structures (Figure 6(b)). With disentanglement loss, the stylized results can preserve unified style patterns and salient content structure.

b) The Influence of Convolutional Receptive Field Size: When calculating the local similarity between disentangled content and style features in CA module, the receptive field size of convolutional operation can influence the generated results. There are two factors that can change the receptive field size. Firstly, the convolution kernel size is fixed to $3 \times 3$ in the encoder, the deeper the model is, the bigger receptive field we can get. Therefore, we use $conv_{5 \times 1}$ replacing $conv_{4 \times 1}$ of the encoder layer to obtain a bigger receptive field. Secondly, in the CA module, we feed the content and style features to two convolutional layers, and calculate their correlation. The convolutional kernel size used in this module is related to the receptive field, which influences the size of the region used to calculate the correlation. Thus, we change the convolutional kernel size from $1 \times 1$ to $3 \times 3$ to obtain a bigger receptive field.

As shown in Figure 7, the stylized results using $conv_{5 \times 1}$ or kernel size $3 \times 3$ are transferred more local style patterns (e.g. circle patterns in the 1st row and feather patterns in the 2nd row), and the content structures are highly distorted. The results prove that bigger receptive field pay more attention to local structure, and will spatially distort global structure.

D. Applications

a) Trade-off between content and style: We can adjust the style patterns weights in the stylized results by changing the $\alpha$ in the following function:

$$I_{cs} = D(\alpha f_{cs} + (1 - \alpha)f_c).$$ (13)

When $\alpha = 0$, we obtain the original content image. When $\alpha = 1$, we obtain the fully stylized image. We change $\alpha$ from 0 to 1, and the results can be seen in Figure 8.

b) Style Interpolation: For more flexible application, we can merge multiple style images into one generated result. Examples are shown in Figure 9. We can also change the weights of different styles.

E. More results

We show more stylized results to verify the effectiveness of our approach in Figure 10. We can conclude that our method can achieve appealing results which can both maintain detailed content structures and rich style patterns.

F. Limitation of our method

Although our method can generate fascinating results in most cases, we may get some unsatisfactory results shown in
Figure 11. When the content structures of a content image are not obvious while the style reference appears monotonous style patterns, our method cannot deal with the local correlation between content and style, and generates unsatisfactory results.

V. CONCLUSIONS AND FUTURE WORK

In this paper, we propose a multi-adaption network to disentangle the global content and style representation, and adjust the style distribution to content distribution by considering the long-range local similarity between the disentangled to content and style features. Moreover, to constrain the separation of style and content features, we propose a disentanglement loss to make the style features independent from the target content feature. Our method can make a trade-off between content structure preservation and style patterns rendering. Adequate experiments show that our network can both consider the global content structure and local style patterns to generate fascinating results. We also analyze the effect of the receptive field size in the convolutional neural network on the generated results.

In future work, we aim to develop a style image selection method to recommend appropriate style images for a given content image based on global semantic similarity of content and style for more practical applications.

REFERENCES

[1] A. A. Efros and W. T. Freeman, “Image quilting for texture synthesis and transfer,” in Proceedings of the 28th Annual Conference on Computer Graphics and Interactive Techniques, 2001, pp. 341–346.

[2] S. Bruckner and M. E. Gröller, “Style transfer functions for illustrative volume rendering.” Computer Graphics Forum, vol. 26, no. 3, pp. 715–724, 2007.

[3] J.-Y. Zhu, T. Park, P. Isola, and A. A. Efros, “Unpaired image-to-image translation using cycle-consistent adversarial networks,” in Proceedings of the IEEE International Conference on Computer Vision. IEEE, 2017, pp. 2223–2232.

[4] L. A. Gatys, A. S. Ecker, and M. Bethge, “Image style transfer using convolutional neural networks,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. IEEE, 2016, pp. 2414–2423.

[5] J. Johnson, A. Alahi, and L. Fei-Fei, “Perceptual losses for real-time style transfer and super-resolution,” in European Conference on Computer Vision (ECCV). Springer, 2016, pp. 694–711.

[6] D. Ulyanov, V. Lebedev, A. Vedaldi, and V. Lempitsky, “Texture networks: Feed-forward synthesis of textures and stylized images,” in International Conference on International Conference on Machine Learning (ICML). JMLR.org, 2016, p. 13491357.

[7] N. Kolkin, J. Salavon, and G. Shakhnarovich, “Style transfer by relaxed optimal transport and self-similarity,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. IEEE, 2019, pp. 10051–10060.

[8] F. Shen, S. Yan, and G. Zeng, “Neural style transfer via meta networks,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. IEEE, 2018, pp. 8061–8069.

[9] Y. Zhi, H. Wei, and B. Ni, “Structure guided photorealistic style transfer,” in Proceedings of the 26th ACM International Conference on Multimedia. ACM, 2018, pp. 365–373.

[10] H. Wu, Z. Sun, and W. Yuan, “Direction-aware neural style transfer,” in Proceedings of the 26th ACM international conference on Multimedia. ACM, 2018, pp. 1163–1171.

[11] L. A. Gatys, A. S. Ecker, M. Bethge, A. Hertzmann, and E. Shechtman, “Controlling perceptual factors in neural style transfer,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. IEEE, 2017, pp. 3985–3993.

[12] Y. Li, C. Fang, J. Yang, Z. Wang, X. Lu, and M.-H. Yang, “Universal style transfer via feature transforms,” in Advances in Neural Information Processing Systems, 2017, pp. 386–396.

[13] Y. Jing, X. Liu, Y. Ding, X. Wang, E. Ding, M. Song, and S. Wen, “Dynamic instance normalization for arbitrary style transfer,” in Thirty-Fourth AAAI Conference on Artificial Intelligence (AAAI). AAAI Press, 2020.

[14] H. Wang, X. Liang, H. Zhang, D.-Y. Yeung, and E. P. Xing, “Zm-net: Real-time zero-shot image manipulation network.” 2017.

[15] D. Y. Park and K. H. Lee, “Arbitrary style transfer with style-attentional networks,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. IEEE, 2019, pp. 5880–5888.

[16] X. Li, S. Liu, J. Kautz, and M.-H. Yang, “Learning linear transformations for fast image and video style transfer,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. IEEE, 2019, pp. 3809–3817.

[17] Y. Yao, J. Ren, X. Xie, W. Liu, Y.-J. Liu, and J. Wang, “Attention-aware multi-stroke style transfer,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. IEEE, 2019, pp. 1467–1475.

[18] S. Gu, C. Chen, J. Liao, and L. Yuan, “Arbitrary style transfer with deep feature reshuffle,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. IEEE, 2018, pp. 8222–8231.

[19] L. Sheng, Z. Lin, J. Shao, and X. Wang, “Avatar-net: Multi-scale zero-shot style transfer by feature decoration,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. IEEE, 2018, pp. 8242–8250.

[20] X. Huang and B. Serge, “Arbitrary style transfer in real-time with adaptive instance normalization,” in Proceedings of the IEEE International Conference on Computer Vision (ICCV). IEEE, 2017, pp. 1501–1510.

[21] T. Q. Chen and M. Schmidt, “Fast patch-based style transfer of arbitrary style,” in Constructive Machine Learning Workshop, NIPS, 2016.

[22] M.-Y. Liu, T. Breuel, and J. Kautz, “Unsupervised image-to-image translation networks,” in Advances in Neural Information Processing Systems, 2017, pp. 700–708.

[23] J.-Y. Zhu, R. Zhang, D. Pathak, T. Darrell, A. A. Efros, O. Wang, and E. Shechtman, “Toward multimodal image-to-image translation,” in Advances in Neural Information Processing Systems, 2017, pp. 465–476.

[24] A. Gonzalez-Garcia, J. Van De Weijer, and Y. Bengio, “Image-to-image translation for cross-domain disentanglement,” in Advances in neural information processing systems, 2018, pp. 1287–1298.

[25] D. Kotovenko, A. Sanakoyeu, P. Ma, S. Lang, and B. Ommer, “A content transformation block for image style transfer,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. IEEE, 2019, pp. 10032–10041.

[26] D. Kotovenko, A. Sanakoyeu, S. Lang, and B. Ommer, “Content and style disentanglement for artistic style transfer,” in Proceedings of the IEEE International Conference on Computer Vision. IEEE, 2019, pp. 4422–4431.

[27] X. Yu, Y. Chen, S. Liu, T. Li, and G. Li, “Multi-mapping image-to-image translation via learning disentanglement,” in Advances in Neural Information Processing Systems, 2019, pp. 2990–2999.

[28] X. Huang, M.-Y. Liu, S. Belongie, and J. Kautz, “Multi-mapping image-to-image translation networks,” in Advances in Neural Information Processing Systems, 2018, pp. 1287–1298.

[29] J. Fu, J. Liu, H. Tian, Y. Li, Y. Bao, Z. Fang, and H. Lu, “Dual attention network for scene segmentation,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). IEEE, 2019, pp. 848–856.

[30] C. Li and M. Wand, “Precomputed real-time texture synthesis with markovian generative adversarial networks,” in European Conference on Computer Vision (ECCV). Springer, 2016, pp. 702–716.
on Computer Vision and Pattern Recognition. IEEE, 2019, pp. 3146–3154.

[32] T.-Y. Lin, M. Maire, S. Belongie, J. Hays, P. Perona, D. Ramanan, P. Dollár, and C. L. Zitnick, “Microsoft coco: Common objects in context,” in European conference on computer vision. Springer, 2014, pp. 740–755.

[33] F. Phillips and B. Mackintosh, “Wiki art gallery, inc.: A case for critical thinking,” Issues in Accounting Education, vol. 26, no. 3, pp. 593–608, 2011.

Yingying Deng received the BSc degree in Automation from University of Science and Technology Beijing in 2017. She is currently working toward the PhD degree in National Laboratory of Pattern Recognition, Institute of Automation, Chinese Academy of Sciences. Her research interests include multimedia analysis, computer vision and machine learning.

Fan Tang received the BS degree in Computer Science from North China Electric Power University in 2013. He is currently working toward the PhD degree in National Laboratory of Pattern Recognition, Institute of Automation, Chinese Academy of Sciences. His research interests include computer graphics, computer vision and machine learning.

Weiming Dong is a Professor in the Sino-European Lab in Computer Science, Automation and Applied Mathematics (LIAMA) and National Laboratory of Pattern Recognition (NLPR) at Institute of Automation, Chinese Academy of Sciences. He received his BSc and MSc degrees in Computer Science in 2001 and 2004, both from Tsinghua University, China. He received his PhD in Computer Science from the University of Lorraine, France, in 2007. His research interests include image synthesis and image recognition. Weiming Dong is a member of the ACM and IEEE.

Feiyue Huang is the director of Social Network Platform Department, Tencent. He received his BSc and PhD degrees in Computer Science in 2001 and 2008, both from Tsinghua University, China. His research interests include image understanding and face recognition.

Changsheng Xu is a Professor in National Lab of Pattern Recognition, Institute of Automation, Chinese Academy of Sciences and Executive Director of China-Singapore Institute of Digital Media. His research interests include multimedia content analysis/indexing/retrieval, pattern recognition and computer vision. He has hold 30 granted/pending patents and published over 200 refereed research papers in these areas. Dr. Xu is an Associate Editor of IEEE Trans. on Multimedia, ACM Trans. on Multimedia Computing, Communications and Applications and ACM/Springer Multimedia Systems Journal. He received the Best Associate Editor Award of ACM Trans. on Multimedia Computing, Communications and Applications in 2012 and the Best Editorial Member Award of ACM/Springer Multimedia Systems Journal in 2008. He served as Program Chair of ACM Multimedia 2009. He has served as associate editor, guest editor, general chair, program chair, area/track chair, special session organizer, session chair and TPC member for over 20 IEEE and ACM prestigious multimedia journals, conferences and workshops. He is IEEE Fellow, IAPR Fellow and ACM Distinguished Scientist.

Wen Sun received the BSc degree in Central South University in 2016. She is currently in the third year of his master’s degree in Institute of Automation, Chinese Academy of Sciences. Her research interests include image understanding and face recognition.