# Neural Abstract Style Transfer for Chinese Traditional Painting

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**Abstract.** Chinese traditional painting is one of the most historical artworks in the world. It is very popular in Eastern and Southeast Asia due to being aesthetically appealing. Compared with western artistic painting, it is usually more visually abstract and textureless, Recently, neural network based style transfer methods have shown promising and appealing results which are mainly focused on western painting. It remains a challenging problem to preserve abstraction in neural style transfer. In this paper, we present a Neural Abstract Style Transfer method for Chinese traditional painting. It learns to preserve abstraction and other style jointly end-to-end via a novel MXDoG-guided filter (Modified version of the eXtended Difference-of-Gaussians) and three fully differentiable loss terms. To the best of our knowledge, there is little work study on neural style transfer of Chinese traditional painting. To promote research on this direction, we collect a new dataset with diverse photo-realistic images and Chinese traditional paintings<sup>6</sup>. In experiments, the proposed method shows more appealing stylized results in transferring the style of Chinese traditional painting than state-of-the-art neural style transfer methods.

**Keywords:** Neural Style Transfer · Chinese Traditional Painting.

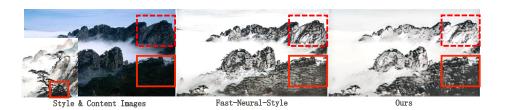
# 1 Introduction

Chinese traditional painting 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.

<sup>&</sup>lt;sup>6</sup> The dataset will be released at https://github.com/lbsswu/Chinese\_style\_transfer.

Recently, convolutional neural network (CNN) [13] 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., an image taken by iPhone. Since the seminal work of Gatys et al. [7], it has attracted a lot of attentions from both academia [10,15,23,24,8,28,31,6,5,4] and industry [26,1,11,3]. 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 Chinese traditional painting.

Unlike western oil paintings which are often concrete and realistic, Chinese traditional freehand painting reveals an 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, textureless and less colorful. And this "abstract style" is not captured well by current neural style transfer methods due to lack of corresponding constraints.



**Fig. 1.** Stylized examples of neural style transfer [7] and our method for Chinese traditional painting. The left column shows the input content image and style image. The middle column shows the transferred result of the neural style transfer method [7]. The right column shows the stylized result of our proposed method. From which we can see, the result generated by our method is more sparse and the style is more like the style image.

Fig. 1 shows an example. The left figure shows an input real image superposed with a Chinese traditional painting as target style. The middle figure shows the stylized result of neural style transfer [10,7] which does not capture the abstract style as concise and clean as the target style image. For instance, trees (solid rectangle) and mountains (dashed rectangle) are not transferred very well, as there are still many redundant edges or stokes on them, which should be abstracted out w.r.t. the style image. Besides, strokes in the stylized results do not align with those in the style image. For example, the style of strokes in the dark area (solid rectangle in the middle figure) stylized by Fast-Neural-Style [10] is still quite different as the one (solid rectangle in the left figure) in the style image, making these areas looks trivial and non-smooth. These comparisons make it clear that we need to learn to "abstract" and keep a smooth and natural transfer that consistent with the style of Chinese traditional painting. This issue has not been addressed in existing methods.

In this paper, we focus on the specific and important problem of style transfer of Chinese traditional painting. Then, to address above issues of current neural style transfer methods, we propose a modified extended difference-of-Gaussians (MXDoG) based style transfer approach for Chinese traditional painting, where a MXDoG filter is utilized to abstract an image. Based on the MXDoG, we formulate three new terms in the loss function for neural style transfer beside the conventional content loss and style loss.

The first loss term is a MXDoG content loss, which penalizes the discrepancy of appearance between the stylized image and the MXDoG filtered image. We suppose the representation of the **abstract content** of an image is also separable along with the **content** and the **style** of the same image, and this loss term will impose a new constraint that requires the stylized image to have a "balanced content" that accommodating to both the "content" and the "MXDoG abstracted content" of an image. The second loss term penalizes the dissimilarity between the MXDoG filtered image of the stylized image and the content image. It is inspired by the work of [17] which uses the Laplacian operator. The third loss term focuses on style, which encourages that the MXDoG filtered image of the stylized image and the style image to have similar styles. The second and third terms are mainly used to penalize large noisy edges in stylized images to make the result more natural. These three loss terms are fully differentiable, thus our style transfer network can be trained end-to-end by stochastic gradient descent method.

An example of our stylized image is shown in Fig. 1(c). Overall, our model shows more appealing style which respects the target style image than neural style transfer methods. For example, our model produces less strokes for the mountain peak in the dashed rectangle than Fast-Neural-Style [10]. This is more in accord with Chinese traditional painting in terms of sparse strokes. In addition, for the dark area (solid rectangle) in the content image, our stylized result is more in accord with the dark area in the style image.

It's worth noted that our method is not necessarily only applicable to Chinese traditional painting. The proposed three new loss terms are used for handling the abstractness and textureless in style transfer, since artworks (e.g., ukiyoe, cartoon, oil painting) have different extents of abstraction, it can work for general art styles by adapting the hyper-parameters of these loss terms. Automatically learning the hyper-parameters is very attractive, we leave it as an interesting future work and focus our efforts on transferring Chinese traditional painting.

To the best of our knowledge, there is no publicly available dataset for evaluating Chinese traditional painting style transfer, thus we collect a new dataset that contains a variety of natural scenes and Chinese traditional paintings. The dataset will be released to facilitate further research on this direction.

In experiments, we compare our method with the neural style methods [7,15,10] on transferring the style of Chinese tradition paintings, and show that our method performs better on transferring image textures, abstract contents, and colors. In addition, the stylized images are "clean", natural and have strong layers of graphics.

We make the following contributions to the community of image style transfer:

- We reintroduce the problem of style transfer of Chinese traditional painting, which poses new challenges and largely omitted by current research.
- We propose a MXDoG filter to abstract the content of an image, and utilize it to transfer the style of Chinese traditional painting.
- We propose three MXDoG based loss terms to guide the neural networks to learn how to "abstract", and demonstrate its effects on test images under different conditions. In this way, we also verify the representations of "abstract content", "content" and "style" of an image can be separated by the neural networks.
- We collect a new Chinese traditional painting dataset to promote the research on style transfer of Chinese traditional painting.

# 2 Related Works

We briefly review related works of neural style transfer and style transfer of Chinese traditional painting below.

Neural Style Transfer. Gatys et al. [7] first propose the neural network based style transfer method, in which they synthesizing images that have the style of one image and the content of another. In their method, the style is represented by the Gram matrix, and the content is represented by high-level convolutional feature maps. Here, the Gram matrix is the global statistics of the image based on outputs from convolutional layers. Gatys's work has received lot of attentions and triggered a whole line of research on deep learning based style transfer. [23,24] investigate several variants of Gatys' method for illumination and season transfer. Li et al. [15] utilize the patch-based Markov random field method to represent the style of the image with neural networks. Luan et al. [21] propose a method for photo to photo style transfer, which shows high quality in photo-realistic.

Recently, Li et al. [17] introduce a Laplacian loss term to preserve detailed content image structures. The key difference between our work and [17] is XDoG vs LoG, rather than DoG vs LoG. DoG (Difference-of-Gaussians) is a fast approximation of the LoG (Laplacian of Gaussians), while XDoG is built on DoG/LoG which detects edges by thresholding DoG responses, rather than searching for the zero crossings in the second derivative (see Eqn. (6)). XDoG is more aesthetically appealing than DoG/LoG due to its effects on **edge enhancement**. Edge enhancement focuses more appropriately on the weight (thickness) and structure (shape) of edges, thus providing better results for stylistic and artistic applications [34].

Fast Neural Style Transfer. Above neural style transfer methods utilize optimization for image style transfer, usually, it takes more than 40 seconds to process an image. Johnson et al. [10] utilize the perceptual loss to train feedforward neural networks, which can be running in real time on GPU. Almost at the same time, Ulyanov et al. [31] propose an unsupervised real time method,

but a multi-scale neural network is used. Li and Wand [16] also propose a feed-forward method to accelerate their patch-based Markov method [15]. Recently, Ulyanov et al. [32] further propose an instance normalization method which significantly improves the quality of fast neural style transfer.

Style Transfer with GAN. Recently, several work [38,16,20,37] try to use or incorporate generative adversarial networks (GAN) for image style transfer. Specifically, the Cycle-GAN method [38] produces amazing results in transferring an image with a painter's style, e.g., Vincent van Gogh, Monet. However, this method is not stable, needs much more time and requires large number of unpaired content and style images for training. What's more, the style of a painting maybe quite different from another even they are painted by the same artist, thus it may be not desirable when we just want to transfer the style of a specific artwork.

Style Transfer for Chinese traditional painting. Before deep neural network is prevalent, many researchers [30,36,33,35,14,2] focus on simulation of the interaction of water, ink, paper and brushes to render Chinese tradition painting. Recently, [18] propose to transfer Chinese painting using multi-scale neural network, however, their method is not end-to-end, and requires sketches or edges for input. Overall, there is little work specifically for style transfer of Chinese traditional painting, thus challenges of style transfer of Chinese traditional painting are largely omitted by our community. In this paper, we make an preliminary analysis of these challenges, and hope more researchers will join and promote the research on this direction.

# 3 Method

We first briefly review the neural style transfer method, then we introduce the modified extended difference-of-Gaussians (MXDoG) filter, which produces a novel representation for image abstraction in our framework. Based on MXDoG, we further introduce the structure and loss functions of our neural network architecture.

# 3.1 Neural Style Transfer

Given a content image  $I_c$  and a style image  $I_s$ , the goal of image style transfer is to generate an image I showing the content of  $I_c$  in the style of  $I_s$ . Gatys et al. [7] formulate the image style transfer as an energy minimization problem which consisting of a content loss and a style loss. Both losses are computed with an ImageNet pretrained object classification network (i.e. VGG-19 [29]).

Inputing an image  $I_c$  to the pre-trained network, we can get the l-th feature map  $F_l(I) = \phi^l(I)$  which corresponds to the response of the l-th layer. The dimension of  $F_l(I)$  is  $N_l \times M_l(I)$ , where  $N_l$  is the number of filters (channels) in the l-th layer, and  $M_l(I) = H_l(I) \times W_l(I)$  is the spatial dimension of the l-th feature map, i.e. the product of its height and width.

With above notations, the objective of neural style transfer method can be represented as follows:

$$L_T(I, I_c, I_s) = \alpha * L_C(I, I_c) + \beta * L_S(I, I_s)$$
 (1)

where  $\alpha$  and  $\beta$  are the weighting factors showing the relative importance of the two components, the content loss is the mean-squared distance between the feature map of  $I_c$  and I at a specified layer l:

$$L_C(I, I_c) = \frac{1}{N_l M_l(I_c)} \sum_{ij} (F_l(I) - F_l(I_c))_{ij})^2$$
 (2)

and the style loss is the mean-squared distance between the correlations of the filter responses (i.e., Gram matrices) of  $I_s$  and I at several appointed layers:

$$L_S(I, I_s) = \sum_{l} \frac{\sum_{ij} (G_{ij}^l(I) - G_{ij}^l(I_s))^2}{N_l^2}$$
 (3)

where  $G_{ij}^l(I) = \frac{1}{M_l(I)} \sum_{k=1}^{M_l(I)} \phi_{ik}^l(I) \phi_{jk}^l(I)$  is the Gram matrix of  $F_l(I)$ . The stylized image is generated by iteratively minimizing Eqn. (1).

Instead of solving an optimization problem, Johnson et al. [10] propose a much faster feed-forward network to directly mapping an input image to the stylized one, this method is called Fast-Neural-Style transfer. Denote the parameters of the feed-forward network as w, the training objective is as follows:

$$w^* = argmin_w E_I[L_T(I, I_c, I_s)] \tag{4}$$

where E is the expectation.

# 3.2 Modified Extended Difference-of-Gaussians



Fig. 2. Filtered results of XDoG, Thresholded XDoG, and MXDoG.

The extended difference-of-Gaussians (XDoG) operators have been shown to yield a range of subtle artistic effects, such as ghosting, speed-lines, negative edges, indication, and abstraction etc [34]. Chinese traditional painting share some similar characters with above artistic paintings, e.g, abstraction, textureless, emphasis of edges. Thus XDoG filters are attractive for us in improving the quality of style transfer for Chinese traditional painting.

Given an image I, traditional XDoG filter can be formulated as:

$$I^{xd} = \mathcal{T}_{\varepsilon,\varphi}(\mathcal{D}_{\sigma,k,\tau}(I)) \tag{5}$$

where  $\mathcal{T}$  is the XDoG filter and  $\mathcal{D}$  is a variant of the difference-of-Gaussians filter in [34].  $\mathcal{T}$  can be formulated by a thresholding funtion with a continuous ramp:

$$\mathcal{T}_{\varepsilon,\varphi}(u) = \begin{cases} 1 & u \ge \varepsilon \\ 1 + \tanh(\varphi \cdot (u - \varepsilon)) & \text{otherwise.} \end{cases}$$
 (6)

where  $\varphi$  and  $\varepsilon$  are the related thresholding parameters. And  $\mathcal D$  can be formulated as

$$D_{\sigma,k,\tau}(x) = g_{\sigma}(x) - \tau \cdot g_{k\sigma}(x) \tag{7}$$

where  $g_{\sigma}(x) = \frac{1}{2\pi\sigma^2} exp(-\frac{\|x\|^2}{2\sigma^2})$  is the Gaussian smoothing filter, k represents a trade-off parameter balancing accurate approximation and adequate sensitivity [22],  $\sigma$  is the standard deviation and  $\tau$  is the control parameter.

Traditional XDoG is aesthetically appealing and can abstract an image to some extent (see Fig 2(b)). However, it's still not enough for general natural images, as there are many small pieces in the image (which is still too detailed). In addition, the XDoG processed image is generally too "white" and is not very compatible with the style of Chinese traditional painting (as the contrast of black and white colors in Chinese traditional painting is generally striking). To this end, we propose a novel modified XDoG (MXDoG) that is a thresholded version of XDoG, and incorporate morphology operations to filter out the small pieces in an image. Our MXDoG is formulated as:

$$I^{md} = morph\_filter(I^{td}) \tag{8}$$

where  $morph_{-}filter$  is the morphology operation which filtering out image regions with their areas smaller than a predefined minimum size  $A_{min}$ , and  $I^{td}$  (Fig. 2(c)) is the thresholded XDoG which is formulated as:

$$I^{td}(x) = \begin{cases} 0 & I^{xd}(x) \le \mu \\ 1, & \text{otherwise.} \end{cases}$$
 (9)

where  $\mu$  is the mean of  $I^{xd}$ .

For a color image, we compute MXDoG for each channel separately. The final result of our MXDoG operator on a sampled image is shown in Fig. 2(d).

### 3.3 Network Architecture

Our style transfer system consists of two components: a generative network and a loss network, as illustrated in Fig. 3. The generative network is responsible for transforming a user-provided image  $I_c$  (as a common practice, we use the

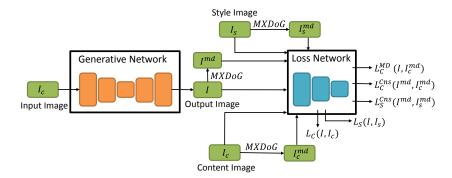


Fig. 3. Network architecture including a generative network and a loss network. As a common practice, we use the content image  $I_c$  as the input image to do style transfer.

content image  $I_c$  as the input image) to a corresponding stylized image. It is a deep residual convolutional neural network with similar network structure as [9]. The loss network is an ImageNet [27] pretrained object classification network, and is fixed during the training of the generative network. Throughout this paper, we use the 16-layer VGG network [29] as the loss network. Besides the content loss and style loss used in [7] and [10], we introduce three new MXDoG-based losses. The generative network is trained using stochastic gradient descent to minimize the following overall loss function:

$$L(I, I_c, I_s, I^{md}, I_c^{md}, I_s^{md}) = \lambda_1 L_C(I, I_c) + \lambda_2 L_C^{MD}(I, I_c^{md}) + \lambda_3 L_S(I, I_s) + \lambda_4 L_C^{Cns}(I^{md}, I_c^{md}) + \lambda_5 L_S^{Cns}(I^{md}, I_s^{md})$$
(10)

Here  $\lambda_i$  is the weighting factors to combine various loss components. The content loss  $L_C$  is computed as Eqn. (2). It is worth noted that although the content loss provides some extent of "abstraction", it is still not enough (see Fig. 1). The style loss  $L_S$  is computed as Eqn. (3). As the styles of traditional Chinese artworks are often textueless and lack of color information, we strengthen the effects of style transfer by using more low-level and high-level layers for style reconstruction than [10]. The implementation details will be exposed in our experiment. Details of our proposed three new loss terms (i.e.,  $L_C^{MD}$ ,  $L_C^{Cns}$ , and  $L_S^{Cns}$ ) are as follows:

**MXDoG Content Loss.** Given content image  $I_c$ , we utilize the MXDoG filter to produce the abstract content image  $I_c^{md}$ . Then  $I_c^{md}$  is used as the input to the loss network to extract high-level features of VGG-16 net. Similar to the content loss, we compute mean-squared Euclidean distance between feature representations  $F_l(I)$  and  $F_l(I_c^{md})$  as:  $L_C^{MD}(I, I_c^{md}) = L_C(I, I_c^{md})$ , In the experiments, we use the same mid-level layer, i.e.,  $relu3_-3$ , for both the content loss and XDoG content loss.

 $L_C^{MD}$  penalizes the output image I when it deviates in content from the target  $I_c^{md}$ . In other words,  $L_C^{MD}$  asks the output image I to have similar appearances

with the MXDoG filtered content image  $I_c^{md}$ . Here  $I_c^{md}$  is used as the "abstract content image".

By providing two content loss: a concrete one  $L_C(I,I_c)$  and an abstract one  $L_C^{MD}(I,I_c^{md})$ , the generative network is encouraged to find a mid-point to balance the fidelity of the photorealistic appearance and the aesthetics of the artistic abstraction. The right figure in Fig. 1 shows a sample result, we can see the generative network indeed learns how to discard some unimportant details (e.g., the mountain peak in the dashed rectangle) when compare with the one produced by the neural style transfer method (the middle figure in Fig. 1) which using the content loss only.

MXDoG Content Constraint Loss. In the stylized image, there are often some noisy edges or distorted artifacts which is inconsistent with the content image. Inspired by [17], we introduce a new loss that constrain  $I^{md}$  to have similar appearances to  $I_c^{md}$ . This loss is defined as the mean-squared distance between  $I^{md}$  and  $I_c^{md}$ , which drives the stylized image to have similar detail structures as the content image. This loss is dubbed as MXDoG content constraint loss as:  $L_C^{Cns}(I^{md}, I_c^{md}) = L_C(I^{md}, I_c^{md})$ , where  $I_c^{md}$  and  $I^{md}$  are computed by Eqn. (8). We use the layer  $relu3_-3$  of VGG16 [29] to get the mid-level patterns and impose the MXDoG content constraint on it.

As MXDoG extracts the "abstract content" of an image, this loss only penalizes the deviation of relatively larger edges or patterns instead of very detail fine structures. This is different from the Laplacian loss used in [17].

MXDoG Style Constraint Loss. In addition to the MXDoG content constraint, we also add a new loss that constrain  $I^{md}$  to have similar styles as  $I_s^{md}$ . The motivation is if the styles of two images are similar, then the styles of their MXDoG filtered images are also similar. As similar to the style loss  $L_S$ , we compute the mean-squared error between the Gram matrices of  $I^{md}$  and  $I_s^{md}$ :  $L_S^{Cns}(I^{md},I_s^{md})=L_S(I^{md},I_s^{md})$ , where  $I_s^{md}$  is also computed by Eqn. (8). This loss further constrains the style consistence of the stylized image and the style image.

# 4 Results

#### 4.1 Implementation Details

Our model builds upon the fast neural style transfer framework of [10], which using the perceptual loss to train feed-forward neural networks to make the stylization achieving real time performance, we only introduces some computational burden on computing the MXDoG loss terms during offline training, and it doesn't adding any extra cost on online testing. The model is trained on the Microsoft COCO database [19], which has around 80k training images. We resize these images to  $256 \times 256$  and train our model using a batch size of 4 for 2 epochs. We adopt Adam [12] for training with a learning rate of  $1 \times 10^{-3}$ . Eqn. (10) is



Fig. 4. Sampled style and content images from the Chinese traditional painting dataset.

utilized as the loss function with the balancing weights  $\lambda_1 = 1.0$ ,  $\lambda_2 = 0.1 \sim 0.3$ ,  $\lambda_3 = 5.0$ ,  $\lambda_4 = 2 \times 10^2$  and  $\lambda_5 = 1 \times 10^3$ . For the computation of our MXDoG, we set  $\tau = 0.94$ ,  $\sigma = 1.0$ , k = 1.6,  $\varphi = 50$ ,  $\varepsilon = -0.1$  and  $A_{min} = 10$ . We compute the content loss at layer  $relu3_{-}3$  and style reconstruction loss at layers  $relu1_{-}2$ ,  $relu2_{-}1$ ,  $relu2_{-}2$ ,  $relu3_{-}1$ ,  $relu3_{-}3$ ,  $relu4_{-}1$  and  $relu4_{-}3$  of the VGG-16 loss network. All the parameters are chosen based on the MS-COCO 2014 validation set. We implement our method using PyTorch [25] with CUDA 7.5 and cuDNN 5.0. It takes about 8 hours to train a model with a single NVIDIA Tesla K40 GPU. After training, our generative network can accept arbitrary input image size, and we resize the input image with the longer edge as 768 before style transfer.

#### 4.2 Chinese traditional painting Dataset

To the best of our knowledge, there is little work study on neural network based Chinese traditional painting style transfer. Thus we collect one with 1000 content images that accommodate to the extent of Chinese traditional painting. These images are collected by web search engines, e.g., Google, Baidu and Bing. They are mostly the photorealistic scenes of mountain, lake, river, bridge, and buildings in regions south of the Yangtze River. It includes not only the scenes of China, but also beautiful pictures of Rhine, Alps, Yellow Stone, Grand Canyon, etc. These images are only used for testing. Besides, we also collect 100 traditional Chinese artworks. These artworks are used as the style images in this paper, which are the typical freehand brush works of China. Some typical style and content images of this dataset are presented in Fig. 4. The whole dataset including all the content and style images will be released to public for further research.

#### 4.3 Baselines

To verify the capability of our model, we compare our method with state-of-theart methods, i.e., Neural-Style Transfer by Gatys et al. [7], Fast-Neural-Style Transfer by Johnson et al. [10], and CNN-MRF by Li and Wand [15]. As they all released their packages, we train their models by using the Chinese traditional painting as style images for comparison. Details will be described in the following.

#### 4.4 Qualitative Results

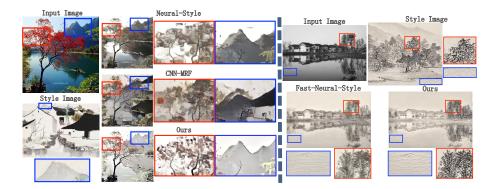
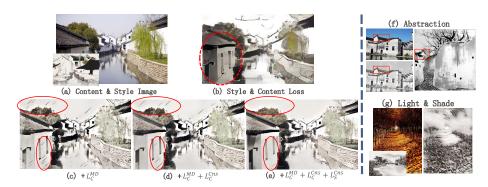


Fig. 5. Left: Comparisons of our method and state-of-the-art Neural-Style [7] and CNN-MRF [15]. Right: Comparisons of our method and Fast-Neural-Style [10].

We compare our method with state-of-the-art methods for a variety of style and content images on Chinese traditional painting dataset. On the left column of Fig. 5, we stylising a photograph with the same artwork for Neural-Style, CNN-MRF and our method. Result of each method is displayed on the right. To analyse the effect of style transfer, we also select two patches and enlarged them for better visualization. From the whole image of the stylized results (the first figure of each method), we can see the Neural-Style method fails to stylize the water. The whole image is a little dark, which may because the optimizationbased method fail to find a good solution to balance the photorealistic content image and the textureless style image. The CNN-MRF method fails to stylize a smooth result, which may because that method requires a good correspondence between content image and style image. For the mountain peak (i.e., the second patch with blue border), we can see the result of our method is most similar to the one (i.e., blue bounding box) in the style image. On the right column of Fig. 5, we compare our method with [10]. From the patches of tree and water, we can see our method presents styles more like ones in the style image.

Besides, we can see the stylized results generated by our method is sparser and have a high contrast, which are more similar to the style image. These results verify the superiority of our method.



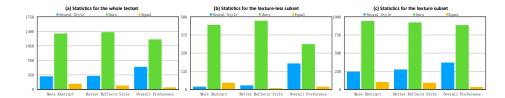
**Fig. 6.** Left: Illustration of effects of our newly introduced losses. (a) style & content images, (b) stylized result of *our base model* that training with only content and style losses as Neural Style [7], (c,d,e) are the results generated by different variants of our model that trained with different MXDoG losses. Right: Two typical failure examples of our method. See text for details.

# 4.5 Ablation Study

Fig. 6 shows an illustration of effects of our three newly introduced losses, i.e., the MXDoG content loss  $L_C^{MD}$ , the MXDoG content constraint loss  $L_C^{Cns}$  and the MXDoG style constraint loss  $L_S^{Cns}$  (we use a high style weight  $\lambda_3 = 100.0$  for verification). Fig. 6(a) shows the style and content images, Fig. 6(b) shows the result generated by our base model that training with only style and content losses ( $L_S$  and  $L_C$ ), this similar to the Neural Style Transfer method [7]. The second column of Fig. 6 shows the stylized results produced by different variants of our model. Specifically, Fig. 6(c) corresponds to the model that trained with only  $L_C$ ,  $L_S$ , and  $L_C^{MD}$ , Fig. 6(d) corresponds to the model that trained with  $L_C$ ,  $L_S$ ,  $L_C^{MD}$ , and  $L_C^{Cns}$ , Fig. 6(e) corresponds our model with full losses. Compare with Fig. 6(b) and Fig. 6(c), we can see, with loss term  $L_C^{MD}$ , the stylized result is more natural and has a higher image contrast (e.g., the building in the dashed ellipse in Fig. 6(b) and Fig. 6(c)), but also introduce some artifacts. By adding loss functions of  $L_C^{Cns}$  and  $L_S^{Cns}$  sequentially, the result is more and more cleaned (refer to the solid ellipses in Fig. 6(c)(d)(e)).

# 4.6 User Study

We carry out a user study to quantitatively evaluate the proposed method. We first randomly select 10 styles of typical Chinese traditional painting, then randomly select 10 stylized images for each style. We invite 60 people, aged from 21 to 45, with diverse educational backgrounds, to participate in our study, each person is asked to cope with 30 randomly selected stylized images, resulting a total of 1,800 trials. In this user study, we compare with the Fast-Neural-Style [10] which can be seen as the fast version of [7]. In each trial, a user is showed with the original image, the style image, and results of [10] and our model.



**Fig. 7.** Results of user study. For each group, the blue bar shows the votes received by Fast-Neural-Style, the green bar shows the votes of our method, and the yellow bar shows the votes of "Equally good or undecided".

The order of the stylized results is randomized to avoid participants' laziness. For each person, we ask three questions: "Which of the two stylized results is more abstract?", "Which of the two stylized results better reflects the style of the painting?", and "Overall, which of the two stylized results do you prefer?". Participants have to select either one of the stylized results or "Equally good or undecided". Overall results of the user study are showed in Fig. 7(a), which indicating a clear preference of our method.

However, as can be seen in Fig. 7(a), there are still some people prefer the result of Fast-Neural-Style [10], thus we make a detailed study about the style patterns.

We first analyse patterns for which the result of our method is preferred by users. We find our model works better on abstract, textureless and less colorful styles. Specifically, it can drop out some tedious details and capture the essence of scenes or objects, which making the whole stylized images looks concise and clean. To verify our observation, we further split the stylized results by the extent of texture and color of style images<sup>7</sup>. Fig 7(b) shows the statistics on results of less textured and colorful styles, and Fig 7(c) shows the statistics on results of textured and colorful styles.

For votes on "More Abstract" and "Better Reflects Style", we can see stylized results of our method are more preferred on transferring less textured and colorful styles. We think this is because more details in the photo are expected to be discarded to match the style of the style image.

However, the preponderance of our method on "Overall Preference" is shrunk, which indicates that although some people think our stylized results are more abstract and closer to the style image, they still like the more concrete images generated by the Fast-Neural-Style. This reflects some inconsistence of "abstraction" and "aesthetical-appealing", and also more powerful method is needed for abstraction, as we can see, the leaves and tree branches on the right of figure 5 is still not good enough as the style image.

<sup>&</sup>lt;sup>7</sup> For instance, figures in the first row of Fig. 4 represent typical examples of textured and colorful style images, while figures in the second row of Fig. 4 stand for the texture-less and less colorful styles.

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# 4.7 Failure Examples

Although our method works well with the general Chinese traditional painting style transfer, we find it still could not achieve the result of a trained human artist in case of "abstraction" and handling the "light and shade". Fig. 6(f) shows our model fails to find the correct correspondence of roof between the content image and the style image. Besides, the roofs in the stylized result should have black colors and curving shapes as the one in the style image, instead of rigid shapes chequered with black and white colors. We think the deep reason is that the neural network is still lack of the human-level "abstraction" capability. Some research [34] show "abstraction" may have strong relevance with the semantic correspondence, thus we believe training a good loss network that can recognize objects and scenes in both photorealistic and artistic images will be a good promising direction. Fig. 6(g) shows our method also fails to stylize images with alternating light and shade. Experiments indicate this is a common failure for all the neural style transfer methods and we leave it as an interesting future work.

# 5 Discussion and Conclusion

Chinese traditional painting is very popular in Eastern Asia, the style of which is often abstract and textureless. This is very different from Western Oil painting, and is not well transferred by current neural style transfer methods [7,10,15]. To tackle this problem, we propose a novel neural style transfer method for Chinese traditional painting. We first introduce a MXDoG filter, then incorporate the MXDoG function with three new loss terms for network training. The effects of our method are verified on test images with diverse conditions. To further promote this research direction, we introduce the Chinese traditional painting dataset which containing diverse content and style images to the public.

Although our method shows superiorities on "abstraction" and in accordance with Chinese traditional painting over current neural style methods, it should be pointed out that the abstraction and aesthetics produced by our model has limitations and does not compete to the one produced by a trained artist. For example, The tree branches stylized by our model in Fig. 5 is still not comparable with ones in the style image. However, as abstraction remains some of the fundamentally unsolved problems in non-photorealistic rendering (NPR) [34], this arguably good results still help a lot for our neural style model to get a freehand painting and might steer deeper research into the artistic neural style transfer community.

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