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Convolutional Neural Network Style Transfer Towards Chinese Paintings

JIACHUAN SHENG [1], CAIFENG SONG [1], JUN WANG [2], AND YAHONG HAN [3], (Member, IEEE)
[1]School of Science and Technology, Tianjin University of Finance and Economics, Tianjin 300222, China
[2]School of Management Science and Engineering, Tianjin University of Finance and Economics, Tianjin 300222, China
[3]College of Intelligence and Computing, Tianjin University, Tianjin 300072, China

Corresponding author: Yahong Han (yahong@tju.edu.cn)

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ABSTRACT Chinese painting is one of the most important cultural heritages. However, creating a Chinese painting usually requires specific skills, patience, and years of professional training. Moreover, most existing style transfer methods mainly focus on photograph or western painting, and there are intrinsic differences between Chinese and western paintings. To this end, we propose a novel algorithm of Chinese painting style transfer (CPST) towards transferring with unique ink and wash characteristics, which automatically generates Chinese paintings with machine learning technology. In this paper, firstly, comparing Chinese paintings with western works, we set up four key restrictions in the style transfer, i.e., with special considerations of typical ink and wash features, including brush stroke, space reservation, ink tone with diffusion and yellowing. In order to incorporate these restrictions into the transferring convolutional neural networks (CNN), we separate different layers of the CNN into layers of style and content, so as to faithfully reserve the style of the reference image. Secondly, as Chinese paintings can be divided into fine brushwork and freehand brushwork, to cope with diverse painting skills, we devise different strategies to transfer not only the ink tone but also the painting skills to the target images. Experiments show that taking the aesthetic characteristics of Chinese painting style as reference, our results are more visually satisfactory and successfully overcome spillovers.

INDEX TERMS Chinese paintings, convolutional neural network, restrictions, style transfer.

I. INTRODUCTION

Over recent years, rapid growth of computer power and technology for database search, digital storage and people's daily access to the Internet have unleashed a wave of innovations, reshaping the way people access cultural heritages and arts. Since traditional Chinese paintings have been regarded as a significant part of the Chinese cultural heritage, their digitalization and processing are becoming a hot topic. Existing research on Chinese paintings mainly focuses on image retrieval and image classification [1]–[3]. However, creating a Chinese painting usually needs specific skills, patience, and years of professional training. How to automatically generate Chinese paintings by using computer technology has become a problem that needs to be solved. Compared with drawing a Chinese artwork, taking a photo is much easier. If we can automatically convert natural images into Chinese paintings, then Chinese paintings will be easy to be achieved.

Style transfer has been widely explored in recent years, which aims to transfer the style of a reference style image to another input picture. Neural Style algorithm [4] is a typical case of style transfer, which has made a strong impression on transferring the style of western paintings. Luan *et al.* [5] introduced semantic and photorealism regularization to guarantee for a realistic generated image. Virtusio *et al.* [6] proposed a method to synthesize the stylized image, which combines a style transfer module with an object segmentation module. Chelaramani *et al.* [7] proposed synthesizes novel renditions of an existing image, conditioned on a given sentence. Luan *et al.* [8] proposed a dedicated algorithm to

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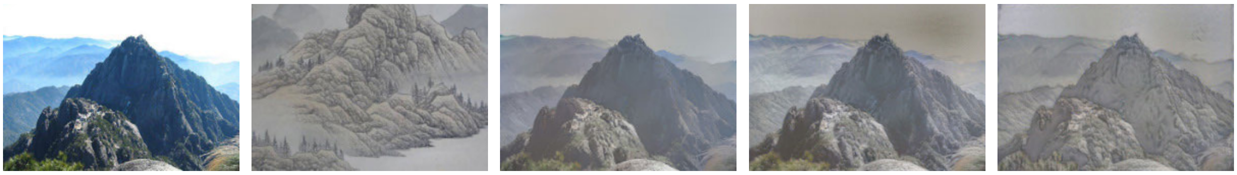

Natural image | Reference Chinese painting | Deep Style | Neural Style | Our result

FIGURE 1. Given a Chinese painting as the reference style image and a natural one as the input image, we aim to automatically create a Chinese painting by transferring the style of Chinese painting to the natural image. Deep and Neural Style algorithms fail to transfer ink tone, and the results lack essential characteristics of Chinese paintings, indicating that these methods are inappropriate in the context of ink and wash style transfer. In contrast, our result faithfully reserves the unique features of Chinese paintings, including brush stroke, ink tone with diffusion, space reservation, and yellowing.

improve photo compositing techniques. Yao *et al.* [9] put forward an attention-aware multi-stroke style transfer model to coordinate the spatial distribution of visual attention between the content image and stylized image.

While extensive research has been done on style transfer of photographs or western paintings, limited research on style transfer of Chinese paintings is carried out from surveying relevant topics in the literature. There are lots of significant differences between western and Chinese paintings. For instance, Chinese paintings are purely executed with the Chinese brush, Chinese ink, mineral, and vegetable pigments, while western arts can be drawn with a variety of tools, mainly including pencil, carbon pen, chalk, watercolor, gouache, and oil paint. In addition, the essential difference between the western paintings and the traditional Chinese paintings lies in the fact that western artists tend to produce their artworks as the actual copy of the painting targets. As a result, western art painting images are very close to natural images. In contrast, Chinese paintings are usually seen as a comprehensive form of art with calligraphy, and most of the Chinese artists used to utilize monochromic ink or gradually changing ink tones to paint. To this end, Chinese painting often expresses its artistic style through brushstrokes and ink tones. Due to such intrinsic differences between Chinese and western paintings, existing methods of western painting cannot be directly applied to Chinese painting style transfer. In Fig. 1, Deep Style and Neural Style algorithms both fail to transfer the ink tone. For example, the trees still keep green, and the results lack essential characteristics of Chinese paintings, indicating that these methods are inappropriate in the context of ink and wash style transfer. Recently, Yang *et al.* [10], [11] proposed a method to generate Chinese flower paintings. However, it is difficult to extend these methods to other kinds of Chinese paintings. From what has been discussed, a novel style transfer algorithm needs to be explored to cope with the unique features of Chinese paintings.

In this paper, we propose a new algorithm of Chinese painting style transfer (CPST) to serve ink and wash paintings. As a result, the generated paintings not only present the characteristics of ink and wash paintings but also preserve the details of the input image. In comparison with the existing style transfer research on the photo or western painting, our technical contributions can be highlighted as 1) a novel CPST algorithm is presented, in which four key restrictions are set up, i.e., with special considerations on the characteristics of Chinese paintings, including brush stroke, ink tone with diffusion, space reservation, and yellowing; 2) to deal with diverse skills of Chinese paintings, different strategies are devised to make the generated Chinese paintings not only transfer ink tone but also transfer painting skills.

The rest of the paper is organized into four sections, where Section 2 focuses on the related work of style transfer. Section 3 mainly presents different strategies when dealing with different skills of reference Chinese paintings and four restrictions are proposed to serve Chinese painting style transfer. While Section 4 reports implementation details, experimental results, and user studies, Section 5 provides concluding remarks.

II. RELATED WORK

Due to the significant advantage of feature learning, Convolutional Neural Network (CNN) is widely explored in computer vision, medical, finance, text processing, and speech recognition [12]–[14]. CNN is firstly used to reconstruct style of famous western paintings on the natural image [15] by Gayts *et al.* Then they further proposed an iteration-based algorithm [4]. Unfortunately, it tends to transfer repetitive style and does not work in real-time. To improve this problem, Johnson *et al.* [16] trained a feed-forward network, which generates similar qualitative images but is three orders of magnitude faster. Ulyanov *et al.* [17] advanced feed-forward texture synthesis and stylization networks. Yin [18] introduced a content-aware algorithm to generate a high-resolution realistic painting. Li and Wand [19] made transfer content-aware by putting forward nearest-neighbor correspondences between neural responses. Odena *et al.* [20] studied the filters used in these networks and explained how to avoid mesh artifacts generated by certain techniques. Risser *et al.* [21] introduced histogram loss to improve the stability of the generated image. Some scholars proposed to replace the Gram matrix with matching other neural response statistics [22], [23]. Liao *et al.* [24] further proposed a bidirectional dense correspondence field matching to improve the quality of the results. Recently, some research emphasized the vital role of local loss in the process of style transfer [25], [26]. Li *et al.* [27] proposed a super-resolution style transfer network to accelerate the style transfer operation and reduce memory usage at run-time. So far, Neural

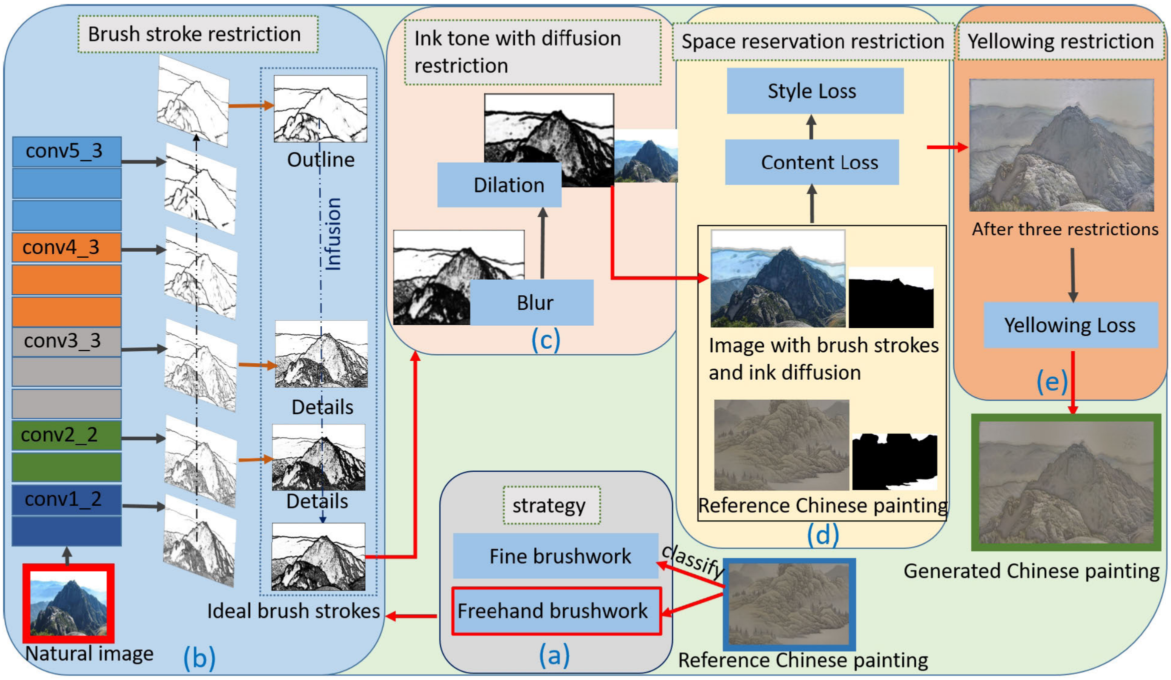

FIGURE 2. The pipeline of our CPST algorithm. We transfer a natural image (highlighted by the red rectangle) into a Chinese painting (highlighted by the green rectangle) by referring a Chinese painting (highlighted by the blue rectangle). (a) A classifier is devised to classify the reference Chinese painting into freehand brushwork and fine brushwork, and thus different reference drawing skills can be identified, which further drives different strategies to serve edge fusion. (b) The brush stroke restriction combines with the weight strategy to get ideal brush strokes of the natural image. (c) Ink tone with diffusion restriction is proposed to simulate ink diffusion on the rice paper by using Gaussian blur and dilation operations. (d) Space reservation restriction is proposed to match with the unique composition of Chinese paintings. (e) The yellowing restriction is presented to express the typical yellowing characteristic of Chinese paintings by adjusting the tone of the whole image.

Style Transfer has been widely used to solve many problems, such as head style transfer [28], video stylization [29], and pose style transfer [30].

III. THE PROPOSED CPST ALGORITHE

In order to put forward an algorithm for Chinese painting style transfer, some significant characteristics of Chinese paintings are summarized by comparing Chinese paintings with western paintings. Kinds of obvious differences are highlighted as 1) Chinese paintings mainly rely on the use of brush strokes with vigorous lines to represent object contour and shape, while western paintings emphasize the use of light to manifest objects and seldom use obvious lines. 2) Chinese paintings essentially contain the same techniques as calligraphy, since they are both made with a brush dipped in black ink or colored pigments. In addition, rice paper and silk are the most popular painting materials. Chinese artists take advantage of ink diffusion on rice paper to express different color levels. While western paintings are usually created on the artboard, and the oil paint is the primary pigment which contains abundant colors. 3) Chinese artists pay great attention to the composition of artworks, and certain space reservation is often used to provide viewers ample imaginary space. Reversely, western paintings are full of colors over the whole image. 4) Most Chinese paintings have a long history and are usually painted on the yellowed rice paper, and thus Chinese paintings are usually yellowing.

From what has been discussed above, we present a novel CPST algorithm to serve Chinese painting style transfer, in which different strategies and four key restrictions are incorporated into the transferring CNN with special considerations on the characteristics of Chinese paintings, including different painting skills, brush stroke, ink tone with diffusion, space reservation, and yellowing.

In our CPST algorithm, the reference Chinese painting is firstly classified into fine brushwork and freehand brushwork. Different strategies are further devised to make sure the generated Chinese paintings not only transfer ink tone but also transfer painting skills. The details are illustrated in Section 3A. Secondly, due to brush stroke is a typical feature of Chinese paintings, we put forward brush stroke restriction in Section 3B. Thirdly, ink tone with diffusion restriction is proposed to simulate ink diffusion in Section 3C. Fourthly, content loss, style loss, and semantic recognition are combined as a restriction to deal with space reservation technique in Section 3D. Fifthly, yellowing restriction is proposed to improve the tone all over the painting in Section 3E. Finally, our final loss function is provided in Section 3F. The complete pipeline of our CPST algorithm is illustrated in Fig. 2.

A. STRATEGIES TOWARDS DIFFERENT PAINTING SKILLS

In terms of painting skills, Chinese paintings can be divided into fine brushwork and freehand brushwork. Fine brushwork requires delicate and meticulous brush strokes, while freehand brushwork pays more attention to extensive and simple brush strokes. It has been shown that, if we ignore different painting skills, the similarity between the style of the generated painting and that of the reference Chinese painting will be significantly weaken. Therefore, our CPST algorithm firstly classifies the reference Chinese painting into fine brushwork and freehand brushwork, which further drives different strategies adopted to serve edge fusion, in order to make the generated skill extremely be similar to that of the reference Chinese painting.

The first step is to devise a classifier which is excellent in the distinction of fine brushwork from freehand brushwork, to identify the painting skill of the reference Chinese painting. The process is shown in Fig. 2(a). In fact, the most obvious difference between fine brushwork and freehand brushwork lies in various degrees of brush strokes. Hence, two strategies with different weight distributions are proposed towards edge fusion in Section 3B.

B. BRUSH STROKE RESTRICTION

Chinese paintings claim to outline their shape based on lines, which usually take advantage of bush strokes to depict the outline, texture, and volume. Compared with Chinese paintings, natural images do not contain any brush strokes. In this paper, we propose a novel CPST algorithm to automatically generate Chinese paintings by style transfer, where the Gram matrix is selected to construct the style model presenting the texture of Chinese ink and wash paintings. However, the generated textures usually tend to be chaotic when the style transfer process purely relies on the Gram matrix. To solve this problem, this paper proposes to integrate proper brush strokes into the natural image to guide the texture distribution during the optimization process.

In the next step, we create unified brush strokes by using holistically nested edge detector (HED) [31]. And then, we propose to calculate five layer edges and a fusion layer, in order to simulate different kinds of brush strokes with different thicknesses.

To get these brush strokes, we firstly input an image I_o into our CPST algorithm, then edge map predictions can be obtained from both the side-output layers and the fusion layer:

$$(\hat{E}_{fuse}, \hat{E}_1, \ldots, \hat{E}_5) = CNN(I_o, W, w, h) \tag{1}$$

where $\hat{E}_{fuse}$ and $\hat{E}_i (i = 1, \ldots, 5)$ represent the map predictions of each layer edge. $CNN(I_o, W, w, h)$ represents the edge maps produced by the detector. W is all standard network layer parameters. The corresponding weights are denoted as w for each side-output layer, and h is the fusion weight. Finally, these generated edge maps are aggregated to get the unified brush strokes.

$$(E_{fuse}, E_1, \ldots, E_5) = Average\ (\hat{E}_{fuse}, \hat{E}_1, \ldots, \hat{E}_5) \tag{2}$$

where E_{fuse} is the final unified fusion edge, $E_i (i = 1, \ldots, 5)$ are the final unified side-output layer edges.

For Chinese paintings, the brush strokes can not only express contours but also reflect the other details, which play a crucial role in the whole paintings. The edges indicate that the fusion layer can well outline contours while the edges of the second and the third side-output layers tend to describe the other brush details inside objects. These edges are further fused by different weight strategies which depend on the classification result of the reference Chinese painting, to fit different Chinese painting skills including fine brushwork and freehand brushwork. The specific strategies are summarized as follows: if the reference style Chinese painting is classified as a fine brushwork painting, the weights of three edges will be set to 0.2, 0.4, and 0.4 respectively to highlight the details. Otherwise, the weights will be set to 0.8, 0.1 and 0.1, respectively. The edges are all pretreated with contrast enhancement before fusion. The ideal brush strokes can be generated by (3), as shown in Fig. 2(b).

$$B_{ideal} = w_1 E_2 + w_2 E_3 + w_3 E_{fuse} \tag{3}$$

where w_1, w_2 and w_3 are the weights of different edges, B_{ideal} is the ideal brush strokes that we need.

C. INK TONE WITH DIFFUSION RESTRICTION

Ideal brush strokes have been obtained by above steps. The next step is to diffuse ink in the generated painting. Most of the traditional Chinese paintings are drawn on the rice paper which is a type of blotting paper, and the ink wash will spread when artists draw on it to express different levels of ink tone. Therefore, ink diffusion plays an important role in simulating Chinese paintings. In our CPST algorithm, Gaussian blur and dilation operations are utilized to simulate ink diffusion, which can be calculated in (4) and (5).

$$B_{blur}(B_{ideal}, x, y, \sigma) = B_{ideal} * \frac{1}{2\pi\sigma} e^{-(x^2+y^2)/2\sigma^2} \tag{4}$$

$$\{B_{ink} | (\hat{A})_{B_{ink}} \cap B_{blur} \neq \emptyset\} = B_{blur} \oplus A \tag{5}$$

where B_{blur} is the output of Gaussian blur operation, and B_{ink} is the output of ink tone with diffusion by further using dilation operation. x, y are the pixel offsets from the original center tap, and σ is the standard deviation of the filter.

As the color distribution of the input image has a significant influence on the effect of style transfer, the brush stroke B_{ink} and the input image I_o are fused at the ratio of 0.25 and 0.75 respectively to obtain an image $I_{B_{ink}}$, which is calculated as follows:

$$I_{B_{ink}}(B_{ink}) = \delta_1 B_{ink} + \delta_2 I_o \tag{6}$$

where δ_1 and δ_2 are the weights of brush stroke and the input image. Taking lotus as an example, the result after each step is shown in Fig. 3.

D. SPACE RESERVATION RESTRICTION

Brush stroke and ink tone with diffusion restrictions have been properly processed, and next we pay attention to the space reservation of traditional Chinese paintings.

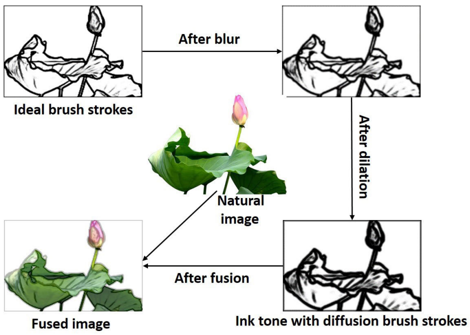

FIGURE 3. To simulate ink diffusion, the ideal brush strokes are blurred and dilated, which are later infused into the input natural image.

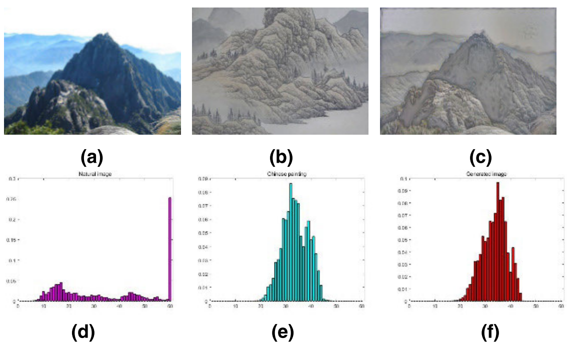

FIGURE 4. (a) is an input natural image, (b) is a reference Chinese painting and (c) is the generated Chinese painting by our method. (d), (e) and (f) are the image histogram of (a), (b), and (c), respectively. By using our style transfer algorithm, the color distribution of the generated image tends to be in accordance with the reference ink and wash style. That is to say, (f) is similar to (e), but it is different from (d).

Chinese artists, on purpose, leave certain space reservation to provide possible space for imagination. Space reservation means appropriately preserving blanks on the canvas [32], which can improve the quality of the whole painting with the effect of "silence is better than sound." Taking Fig. 4 for an example, appropriately applying space reservation requires the generated image ignoring the background of the input image while obviously keeping the silhouettes of the mountain. Since the natural image and the Chinese painting have different color distribution, the histogram of the natural image is quite different from that of the reference Chinese painting and the generated Chinese painting, as shown in Fig. 4. How to deal with the different color distribution between the source image and target image, and how to convert the background of a source image into a space reservation effect become important issues for Chinese painting style transfer. Inspired by Deep Style algorithm [5], we separate different layers of the convolutional neural network into style and content. And then, we propose our content loss and style loss by setting the same semantics for the space reservation of the reference painting and that of the input image to accurately transfer the characteristics of the space reservation to the natural image.

Content loss $L^{\ell}_{content}$ is proposed to preserve the shape and details of the key objects. Style loss L^{ℓ}_{style} is proposed to deal with Chinese painting style. The proposed content loss and style loss are respectively computed as follows:

$$L^{\ell}_{content}(I_{B_{ink}}) = \frac{1}{2N_\ell D_\ell}\sum_{ij}(F_\ell[O_{output}] - F_\ell[I_{B_{ink}}])^2_{ij} \quad (7)$$

$$L^{\ell}_{style+} = \sum_{c=1}^{C}\frac{1}{2N^2_{\ell,c}}\sum_{ij}(G_{\ell,c}[O_{output}] - G_{\ell,c}[S_{style}])^2_{ij} \quad (8)$$

where ℓ represents the $\ell - th$ convolutional layer of the convolutional neural network. N_ℓ is the number of filters, and each filter with a vectorized feature map of size D_ℓ. $F_\ell[\cdot] \in \mathbb{R}^{N_\ell \times D_\ell}$ is the feature matrix with (i, j) indicating its index, O_{output} is the output image in each channel. C is the number of channels in the semantic segmentation mask, and S_{style} is the reference Chinese painting. The Gram matrix $G_{\ell,c}[\cdot] = F_{\ell,c}[\cdot]F_{\ell,c}[\cdot]^T \in \mathbb{R}^{N_\ell \times D_\ell}$ is defined as:

$$F_{\ell,c}[O_{output}] = F_\ell[O_{output}]M_{\ell,c}[I_{B_{ink}}] \quad (9)$$

$$F_{\ell,c}[S_{style}] = F_\ell[S_{style}]M_{\ell,c}[S_{style}] \quad (10)$$

where $M_{\ell,c}[\cdot]$ denotes the channel c of the segmentation mask in layer ℓ.

E. YELLOWING RESTRICTION

Yellowing is one of the essential characteristics of Chinese paintings. The reason lies in the facts that: 1) Chinese paintings are created on the yellowed rice paper; 2) ink and wash paintings have a long history and most of them were created in ancient, which leads to color distortion; 3) in terms of composition, there are certain space reservation in most Chinese paintings, which usually express yellowing. Consequently, to simulate the tone of yellowing, we finally propose yellowing restriction.

In this paper, a novel yellowing loss is proposed in the CPST algorithm to simulate yellowing tone. Since the Gram matrix is insensitive to the specific distribution of style, some unstable drawbacks are shown when dealing with yellowing tone. For instance, there are two images with different mean and variance but with the same Gram matrix value. To enforce the stability of the Gram matrix, histogram loss method is proposed to optimize the generated image tone by improving the final loss function, which can better present the yellowing characteristic of Chinese paintings. The novel yellowing loss $L^{\ell}_{yellowing}$ is calculated as follows:

$$L^{\ell}_{yellowing} = \sum_{\ell=1}^{L}\lambda_\ell\sum_{i=1}^{N_\ell}\sum_{p=1}^{D_\ell}(F_\ell[O_{output}] - R_\ell[O_{output}])^2_{ip} \quad (11)$$

with: $R_\ell[O_{output}] = tonematch(F_\ell[O_{output}], F_\ell[S_{style}])$ (12)

where L is the total number of convolutional layers, λ_ℓ is the weight of each layer and $R_\ell[O_{output}]$ is the yellowing-remapped feature map by matching $F_\ell[O_{output}]$ to $F_\ell[S_{style}]$.

F. FINAL LOSS FUNCTION OF CPST

Considering the brush stroke restriction and the ink tone with diffusion restriction have been incorporated into the image $I_{B_{ink}}$, our final loss function L_{final} can be computed as a linear combination of content loss $L^{\ell}_{content}$, style loss L^{ℓ}_{style}, and yellowing loss $L^{\ell}_{yellowing}$. Our new loss function L_{final} contains four restrictions, including brush stroke, ink tone with diffusion, space reservation and yellowing. In our CPST algorithm, the typical characteristics of Chinese paintings are taken into account to the greatest extent. The specific formula is computed as follows:

$$L_{final}(I_{B_{ink}}) = \sum_{\ell=1}^{L} \mu_{\ell} L^{\ell}_{content} + w_{style} \sum_{\ell=1}^{L} \eta_{\ell} L^{\ell}_{style} + w_{yellowing} \sum_{\ell=1}^{L} \gamma_{\ell} L^{\ell}_{yellowing} \tag{13}$$

where μ_{ℓ}, η_{ℓ} and γ_{ℓ} are the weights to configure layer preferences. w_{style} is a weight that controls the style loss. $w_{yellowing}$ is a weight that controls the yellowing loss.

IV. EXPERIMENTS

A. IMPLEMENTATION DETAILS

In our experiments, the pre-trained VGG-19 [33] is employed to extract features. Layer4_2 ($\mu_{\ell} = 1$ for layer4_2, and $\mu_{\ell} = 0$ for all the other layers) is selected to represent the content; layer1_1, layer2_1, layer3_1, layer4_1 and layer5_1 ($\eta_{\ell} = 1/5$ for these layers, and $\eta_{\ell} = 0$ for all the other layers) are selected to represent the style; layer1_1 and layer4_1 ($\gamma_{\ell} = 1/2$ for these layers, and $\gamma_{\ell} = 0$ for all the other layers) are selected to represent yellowing. We used these layer preferences and parameters $w_{style} = 10^4$, $w_{yellowing} = 1$ for all the results.

Our work is carried out on Ubuntu 14.04, which mainly depends on Torch and CUDA. CUDA is used to deal with feature activation in the VGG network. The optimization pipeline is implemented by torch. L-BFGS solver is used for the reconstruction with 1000 iterations. All our experiments are conducted on a PC with an Intel Xeon processor and NVIDIA Quadro K1200 GPU.

B. RESULTS AND COMPARISON

In Chinese paintings, fine brushwork and freehand brushwork are two entirely different painting techniques. To sufficiently transfer the style of ink and wash painting, Our CPST algorithm claims to transfer both painting skills and ink tone to the natural image. A classifier is trained to classify different painting techniques by GoogLeNet V3, namely fine brushwork and freehand brushwork, where 2500 pictures serve as the training dataset, and 600 pictures serve as the test dataset. The classification results show that the average recall rate and the precision rate are 0.975, 0.918, respectively. The high accuracy of classification results provides a good guarantee for subsequent experiments.

To benchmark the proposed algorithm, we visually compare our CPST method against four representative algorithms, including Neural Style [4], Deep Style [5], IN Style [17], and WCT [23] algorithms, as shown in Fig. 5. Those algorithms have successfully transferred the style of western paintings or photos. However, when they solve style transfer tasks towards Chinese painting, they fail to generate satisfying results, since they are insensitive to the style of Chinese ink and wash paintings. The images generated by Neural Style and IN Style algorithms are similar to their original input images in the row (d). Deep Style algorithm fails to transfer ink tone to some important parts (highlighted by the red rectangle) in row (c). In contrast, our results not only preserve contours of objects but also successfully transfer the style of the reference ink and wash painting to the whole natural image.

In comparison with four benchmarks, the proposed CPST algorithm outperforms the existing methods and delivers considerably better results on brush stroke, ink tone with diffusion, space reservation and yellowing across all the cases, shown as Fig. 5. In view of brush stroke (highlighted by the red rectangles in the row (f)), the reference Chinese painting contains fine and delicate brush strokes. Unfortunately, the four results of benchmarks do not contain any brush strokes. In comparison, our CPST algorithm successfully transfers the brush strokes to the generated painting. In view of ink tone with diffusion (highlighted by red rectangles in the row (c)), the benchmarks fail to transfer ink tone to the lotus leaf. In contrast, our CPST result not only transfers ink tone but also presents different ink levels. In view of space reservation (highlighted by red rectangles in the row (a)), the textures generated by Deep Style, IN Style, and WCT algorithms are too smooth, which are inappropriate in the context of ink and wash paintings style transfer. Besides, the Neural Style algorithm suffers from spillovers, e.g., with the space reservation taking on the style of the mountain. By comparison, our result perfectly reproduces the space reservation of the reference Chinese painting. In view of yellowing, compared with benchmarks in the row (d), the tone of our result is much closer to that of the reference Chinese painting. From what has been discussed above, our results are more visually satisfying according to the aesthetic characteristics of Chinese paintings, which demonstrates the proposed restrictions, including brush stroke, ink tone with diffusion, space reservation and yellowing are effective.

To verify the proposed CPST algorithm applies to most Chinese painting scenes, we conduct our experiments across a series of scenes, including landscapes, flowers, birds, fruits, and animals et al., which often appear in traditional Chinese paintings. As shown in Fig. 5. Our CPST algorithm performs well in these scenes, and the results significantly advance the state-of-the-art. There are also some special cases of Chinese painting style transfer. 1) When the content of the reference Chinese painting is different from that of the natural image, the transfer result can be controlled by providing the semantic masks, e.g., to match a transplant apple to gourd in the row (g). Compared with benchmarks, our generated painting is

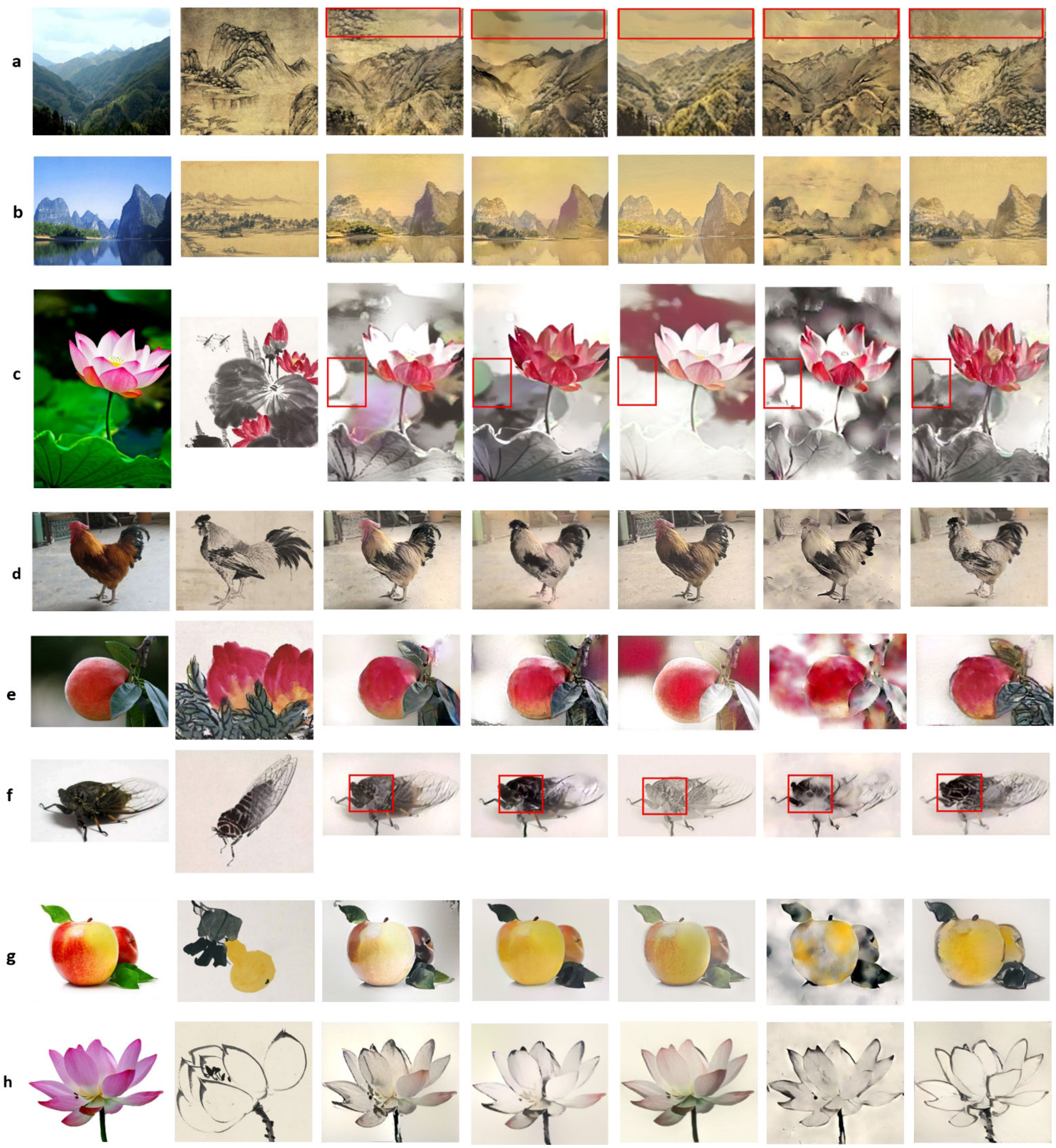

FIGURE 5. Comparison of our CPST method against Neural Style [4], Deep Style [5], IN Style [17], and WCT [23].

more visually satisfying. However, our CPST algorithm is semantic based. Therefore, the great difference between the content of input image and that of reference Chinese painting is not encouraged, in order to generate high-quality Chinese paintings. 2) When the reference Chinese painting is an outlined painting, the CPST algorithm also performs better than the other algorithms, as shown in the row (h).

In Fig. 6, the ablation experiment is designed to prove that all the proposed restrictions are valid and indispensable. Firstly, the result generated by our CPST algorithm is given in Fig. 6(a), taking full account of all four restrictions. Secondly, in Fig. 6(b), the space reservation restriction is removed, which results in spillovers, with the space reservation taking on the style of the lotus leaf (highlighted by the

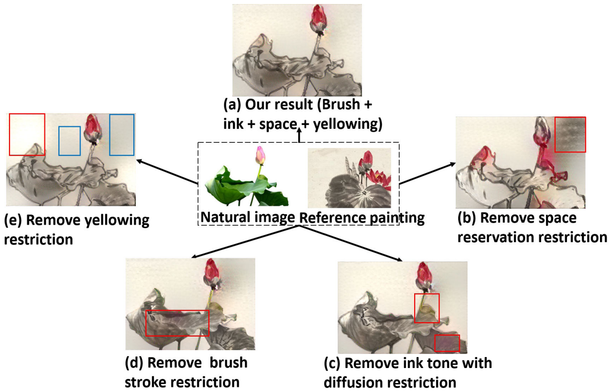

FIGURE 6. To verify all the proposed restrictions are valid and indispensable, an ablation experiment is designed. The experiment results show that no matter which restriction is removed, the typical characteristics of Chinese paintings will be greatly destroyed in the generated painting.

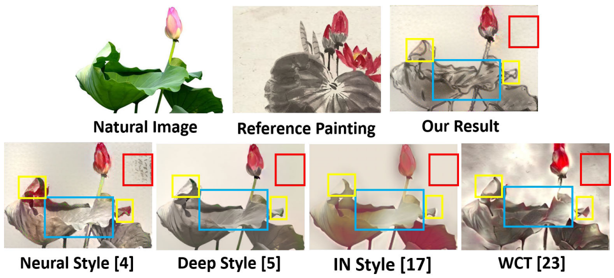

FIGURE 7. An example is given to compare our algorithm with benchmarks to verify the four restrictions we proposed play an important role in Chinese painting style transfer.

red rectangle). Thirdly, in Fig. 6(c), the ink tone with diffusion restriction is removed. The results show that the areas (highlighted by the red rectangles) poorly reflect ink tone, even smudging with green and pink. Fourthly, in Fig. 6(d), the brush stroke restriction is removed, which leads to the absence of typical brushwork characteristics in the generated image. Finally, in Fig. 6(e), the yellowing restriction is removed. The result is mixed with white and gray tones (highlighted by the red and blue rectangles). In a word, the experiment results reveal that no matter which restriction is removed, the typical feature of Chinese paintings will be significantly destroyed in the generated painting.

In Fig. 7, we further compare our CPST algorithm with benchmarks more specifically. The experiment results show that the benchmarks lack obvious brush strokes (highlighted by blue rectangles). They also poorly reflect ink tone, even smudging with green and pink in the generated paintings (highlighted by yellow rectangles). Moreover, some noise appears in the space reservation (highlighted by red rectangles). In contrast, the typical features of Chinese paintings perform better in our result, including brush stroke, ink tone with diffusion, and space reservation. In addition, the yellowing tone of our result is much closer to that of the reference painting than the other methods.

In our CPST algorithm, different strategies are proposed to deal with different skills of the reference Chinese paintings.

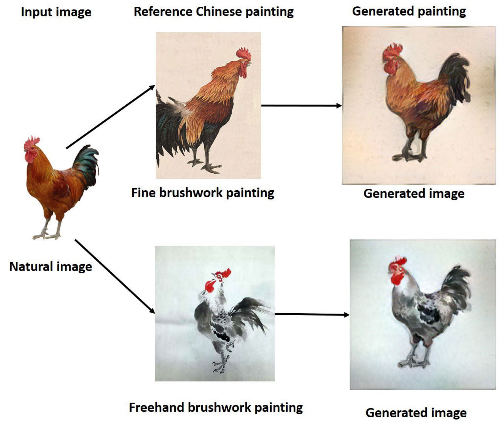

FIGURE 8. For a given input natural image, when different reference styles are specified, our algorithm successfully generates corresponding results of different Chinese painting skills.

As a result, for a given input natural image, when different reference styles are specified, our algorithm will generate corresponding results of different Chinese painting techniques, as shown in Fig. 8. That is to say, when the reference Chinese painting is a fine brushwork, the output painting will be visually described with fine, delicate strokes. Otherwise, the generated painting will use extensive, concise strokes to depict objects. Hence, Fig. 8 demonstrates that the strategy employed in our algorithm is valid.

C. USER STUDIES

In this section, three user studies are designed from different perspectives to evaluate our CPST algorithm. Firstly, 30 students are invited to score the stylization perception of several techniques. Secondly, ten artists are invited to assess the generated paintings from the criteria of brush stroke, ink tone with diffusion, space reservation, yellowing, and global ink-wash style, respectively. Finally, we further invite these artists to score the generated paintings with meticulous attention to ink techniques and coloring, including yin and yang, dry and wet, asthenia and sthenia, dense dilute, ink wash, coloring, Gou, Cun, dot, and diffusion.

We firstly evaluate the stylization perception of several techniques (our CPST algorithm, Neural Style [4], Deep Style [5], IN Style [17], and WCT [23]) with 30 students. The participants are asked to score images on a scale of 1 to 5, ranging from "bad" to "excellent." There are 10 different cases for each of the five methods used for a total of 50 questions. Fig. 9 summarizes the average scores of the study by different methods based on the evaluation of students. The average score of the test reflects the style similarity of the generated paintings to the style of the reference Chinese paintings. Our CPST algorithm obtains the highest score, which demonstrates that the proposed four restrictions make great contributions to transfer the typical features of Chinese paintings. In addition, the scores of the IN Style and the WCT are very low, which indicates that they fail to transfer the style of Chinese paintings.

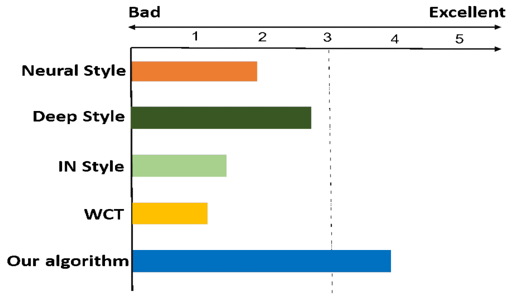

FIGURE 9. User study results proving that our paintings better reflect the style of reference Ink and wash painting.

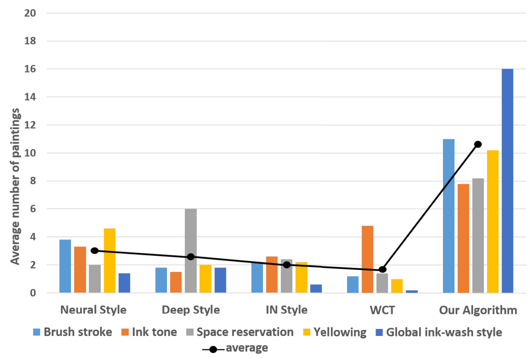

FIGURE 10. Ten artists take part in our user study to evaluate the generated paintings according to brush stroke, ink tone, space reservation, yellowing, and global ink-wash style, respectively. The results show that our algorithm overcomes benchmarks in dealing with both an individual concrete feature and the global perspectives of Chinese art.

The second study is designed to evaluate the generated paintings from a more professional perspective. Ten artists are invited to join our user study, five of them work in Tianjin Academy of Fine Arts and the other five artists work in the Art Department of Tianjin University of Finance and Economics. In this study, 20 groups of pictures are provided. Each group consists of a natural image, a reference Chinese painting, and five Chinese paintings generated by different algorithms (Our CPST algorithm, Neural Style [4], Deep Style [5], IN Style [17], and WCT [23]). In this study, the five generated paintings are randomly disordered in each group, and the style transfer method of each painting is invisible to artists. The artists are asked to select one of the most satisfying Chinese painting from each group on the criteria of brush stroke, ink tone, space reservation, yellowing, and global ink-wash style, respectively. Fig. 10 summarizes the average number of paintings selected for each algorithm based on the assessment of the artists, which indicates that our CPST algorithm overcomes benchmarks in dealing with both an individual concrete feature and the global perspectives of Chinese art. Especially, when the artists are asked to select the paintings that best reflect the brush stroke of Chinese paintings, the images generated by our CPST algorithm are selected at the highest ratio, which reveals the proposed CPST algorithm best follows the principle of ''line and brush stroke modeling''. In addition, in view of the global ink-wash style, our CPST algorithm also produces the most faithful ink and wash style.

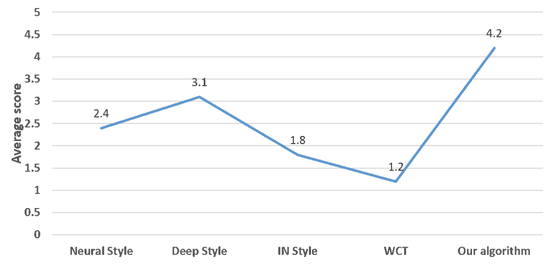

FIGURE 11. Evaluation results indicate that our paintings can also well reflect the characteristics of traditional Chinese painting from details.

For the final study, to evaluate the generated paintings with meticulous attention to ink techniques and coloring, 30 questions are designed from the aspects of yin and yang, dry and wet, asthenia and sthenia, dense dilute, ink wash, coloring, Gou, Cun, dot, and diffusion. In this study, the reference images are not shown to the artists, so that the artists could focus on the generated paintings. There are 10 different paintings for each of the five methods, and the artists are asked to score for the paintings on a scale of 1 to 5, ranging from ''bad'' to ''excellent''. The average scores of the five algorithms are shown in Fig. 11. Evaluation results indicate that our paintings can also well reflect the characteristics of traditional Chinese painting from details. Besides, the artists emphasize that our paintings give people an antique feeling from the tone. They believe our work will bring new opportunities to develop Chinese painting.

V. CONCLUSION

In this paper, we propose a novel CPST algorithm that paves the way to convert a photo into a Chinese painting automatically, in which four key restrictions are set up, i.e., with special considerations on the characteristics of Chinese paintings, including brush stroke, ink tone with diffusion, space reservation, and yellowing. Besides, different strategies are proposed so that the generated Chinese paintings not only transfer ink tone but also transfer painting techniques. Compared with other algorithms, our CPST algorithm shows better performance in various Chinese paintings. Moreover, it has a range of impacts and values, which include: 1) combination of image processing, deep learning and creative arts to explore a new field of research on digital arts; 2) provision of computing support for cultural and artistic inheritance.

While experimental results support that the proposed CPST algorithm outperforms the existing benchmarks, including Neural Style [4], Deep Style [5], IN Style [17], and WCT [23], indicating a significant progress toward style transfer of traditional Chinese arts, there exist enormous potential and space for further improvements, which can be highlighted as follows: fundamental tests show that our CPST algorithm cannot be applied to figure paintings directly. The most difficulties lie in the abundant expressions and postures of figures. Besides, in ancient Chinese figure paintings, the five sense organs are often processed by art creation on shapes based on ancient aesthetics, such as slender Danfengyan, cherry mouth, et al. However, our CPST algorithm aims to transfer the style of the reference Chinese painting to the input image without changing its shape. In the future, we will further improve the CPST algorithm to serve figure paintings, so that the generated paintings can not only transfer the ink tone and painting skills but also transfer the artistic shapes according to ancient aesthetics.

REFERENCES

[1] J. Sheng and J. Jiang, ''Recognition of Chinese artists via windowed and entropy balanced fusion in classification of their authored ink and wash paintings (IWPs),'' *Pattern Recognit.*, vol. 47, no. 2, pp. 612–622, 2014.

[2] J. Sheng and Y. Li, ''Classification of traditional Chinese paintings using a modified embedding algorithm,'' *Proc. SPIE*, vol. 28, no. 2, 2019, Art. no. 023013.

[3] J. Sheng and J. Jiang, ''Style-based classification of Chinese ink and wash paintings,'' *Proc. SPIE*, vol. 52, no. 9, pp. 093101-1–093101-8, 2013.

[4] L. A. Gatys, A. S. Ecker, and M. Bethge, ''Image style transfer using convolutional neural networks,'' in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2016, pp. 2414–2423.

[5] F. Luan, S. Paris, E. Shechtman, and K. Bala, ''Deep photo style transfer,'' in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2017, pp. 6997–7005.

[6] J. J. Virtusio, A. Talavera, D. S. Tan, K.-L. Hua, and A. Azcarraga, ''Interactive style transfer: Towards styling user-specified object,'' in *Proc. IEEE Vis. Commun. Image Process. (VCIP)*, Taichung, Taiwan, Dec. 2018, pp. 1–4.

[7] S. Chelaramani, A. Jha, and A. M. Namboodiri, ''Cross-modal style transfer,'' in *Proc. IEEE Int. Conf. Image Process. (ICIP)*, Athens, Greece, Oct. 2018, pp. 2157–2161.

[8] F. Luan, S. Paris, E. Shechtman, and K. Bala, ''Deep painterly harmonization,'' *Comput. Graph. Forum*, vol. 37, no. 4, pp. 95–106, 2018.

[9] Y. Yao, J. Ren, X. Xie, W. Liu, Y.-J. Liu, and J. Wang, ''Attention-aware multi-stroke style transfer,'' in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2019, pp. 1467–1475.

[10] L. Yang, T. Xu, J. Du, and E. Wu, ''Sketch-based stroke generation in Chinese flower painting,'' *Sci. China Inf. Sci.*, vol. 59, no. 7, 2016, Art. no. 079101.

[11] L. Yang, T. Xu, J. Du, and E. Wu, ''Easy drawing: Generation of artistic chinese flower painting by stroke-based stylization,'' *IEEE Access*, vol. 7, pp. 35449–35456, 2019.

[12] W. Liu, Z. Wang, X. Liu, N. Zeng, Y. Liu, and F. E. Alsaadi, ''A survey of deep neural network architectures and their applications,'' *Neurocomputing*, vol. 234, pp. 11–26, Apr. 2017.

[13] L. Zhao, Q. Sun, and Z. Zhang, ''Single image super-resolution based on deep learning features and dictionary model,'' *IEEE Access*, vol. 5, pp. 17126–17135, 2017.

[14] G. Wang, ''A perspective on deep imaging,'' *IEEE Access*, vol. 4, pp. 8914–8924, 2016.

[15] L. A. Gatys, A. S. Ecker, and M. Bethge, ''A neural algorithm of artistic style,'' 2015, *arXiv:1508.06576*. [Online]. Available: https://arxiv.org/abs/1508.06576

[16] J. Johnson, A. Alahi, and L. Fei-Fei, ''Perceptual losses for real-time style transfer and super-resolution,'' in *Proc. Eur. Conf. Comput. Vis. (ECCV)*, 2016, pp. 694–711.

[17] D. Ulyanov, A. Vedaldi, and V. Lempitsky, ''Improved texture networks: Maximizing quality and diversity in feed-forward stylization and texture synthesis,'' in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jul. 2017, pp. 6924–6932.

[18] R. Yin, ''Content aware neural style transfer,'' 2016, *arXiv:1601.04568*. [Online]. Available: https://arxiv.org/abs/1601.04568

[19] C. Li and M. Wand, ''Combining Markov random fields and convolutional neural networks for image synthesis,'' in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2016, pp. 2479–2486.

[20] A. Odena, V. Dumoulin, and C. Olah, ''Deconvolution and checkerboard artifacts,'' *Distill*, vol. 1, no. 10, p. e3.2, 2016.

[21] E. Risser, P. Wilmot, and C. Barnes, ''Stable and controllable neural texture synthesis and style transfer using histogram losses,'' 2017, *arXiv:1701.08893*. [Online]. Available: https://arxiv.org/abs/1701.08893

[22] X. Huang and S. Belongie, ''Arbitrary style transfer in real-time with adaptive instance normalization,'' in *Proc. IEEE Int. Conf. Comput. Vis. (ICCV)*, Jun. 2017, pp. 1501–1510.

[23] Y. Li, C. Fang, J. Yang, Z. Wang, X. Lu, and M.-H. Yang, ''Universal style transfer via feature transforms,'' in *Proc. Adv. Neural Inf. Process. Syst*, 2017, pp. 386–396.

[24] J. Liao, Y. Yao, L. Yuan, G. Hua, and S. B. Kang, ''Visual attribute transfer through deep image analogy,'' *ACM Trans. Graph*, vol. 36, no. 4, 2017, Art. no. 120.

[25] H.-H. Zhao, P. L. Rosin, Y.-K. Lai, M.-G. Lin, and Q.-Y. Liu, ''Image neural style transfer with global and local optimization fusion,'' *IEEE Access*, vol. 7, pp. 85573–85580, 2019.

[26] Y. Liu, Z. Xu, W. Ye, Z. Zhang, S. Weng, C.-C. Chang, and H. Tang, ''Image neural style transfer with preserving the salient regions,'' *IEEE Access*, vol. 7, pp. 40027–40037, 2019.

[27] Z. Li, F. Zhou, L. Yang, X. Li, and J. Li, ''Accelerate neural style transfer with super-resolution,'' *Multimedia Tools Appl.*, 2019, doi: 10.1007/s11042-018-6929-x.

[28] J. Fišer, O. Jamriška, D. Simons, E. Shechtman, J. Lu, P. Asente, M. Lukáč, and D. Sýkora, ''Example-based synthesis of stylized facial animations,'' *ACM Trans. Graph.*, vol. 36, no. 4, p. 155, 2017.

[29] M. Ruder, A. Dosovitskiy, and T. Brox, ''Artistic style transfer for videos and spherical images,'' *Int. J. Comput. Vis.*, vol. 126, no. 11, pp. 1199–1219, 2018.

[30] N. Neverova, R. A. Guler, and I. Kokkinos, ''Dense pose transfer,'' in *Proc. Eur. Conf. Comput. Vis. (ECCV)*, Jun. 2018, pp. 123–138.

[31] S. Xie and Z. Tu, ''Holistically-nested edge detection,'' in *Proc. IEEE Int. Conf. Comput. Vis. (ICCV)*, Jun. 2015, pp. 1395–1403.

[32] D.-W. Kwo, *Chinese Brushwork in Calligraphy and Painting: Its History, Aesthetics, and Techniques*. New York, NY, USA: Dover, 1990.

[33] K. Simonyan and A. Zisserman, ''Very deep convolutional networks for large-scale image recognition,'' 2014, *arXiv:1409.1556*. [Online]. Available: https://arxiv.org/abs/1409.1556

JIACHUAN SHENG received the Ph.D. degree in computer science from Tianjin University, in 2013. From February 2017 to February 2018, she visited UMass Boston, as a Visiting Scholar. She is currently an Associate Professor with the Tianjin University of Finance and Economics. She is also a Master Tutor. Her research interests include digital media processing via image processing, video processing approaches, and pattern recognition.

CAIFENG SONG is currently pursuing the degree with the Tianjin University of Finance and Economics. Her research interests include image processing and machine learning.

JUN WANG is currently an Associate Professor with the Tianjin University of Finance and Economics. He is also a Master Tutor. His research interest includes intelligent optimization algorithm and application.

YAHONG HAN (M'15) received the Ph.D. degree in computer science from Zhejiang University. In 2012, he joined the School of Computer Science and Technology, Tianjin University, as an Associate Professor. From November 2014 to November 2015, he visited Prof. B. Yu's Group at UC Berkeley, as a Visiting Scholar. He is currently a Full Professor with Tianjin University. His research interests include multimedia analysis and retrieval, computer vision, and machine learning.