

An adjustable visual effect approach for neural stylized images

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ABSTRACT

Neural style transfer (NST), a technique based on deep learning of convolution neural network (CNN) to create entertaining pictures by cleverly stylizing ordinary pictures with the predetermined visual art style, has recently become a widely employed approach to produce various styles for the purpose of training in art education and industrial applications. The effect of the neural style is often visually impressive; however, three issues must be carefully investigated during the generation of neural-stylized artwork. First, it is found that the stylized image may appear over-stylized accidentally. Second, the predefined content-style weighting may be unsuitable for certain styles. The resetting/re-training is then required to obtain a satisfactory result. Third, the stylized images often have low-contrast problems. To solve these issues, we propose a fast and versatile post-processing framework based on image fusion, contrast enhancement, and blending technique. This work provides a window-based program to validate the proposed approach with three experiments which show that the framework can render the stylized images more visual-pleasing effect.

Keywords: blending technique, brovey transform (BT), deep learning, neural style transfer (NST), intensity conservation direct decorrelation stretch (ICDDS)

一個可調整神經風格影像視覺效果的方法

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摘 要

神經風格轉換是一種基於深度學習的卷積神經網路，將一張普通圖片與一張藝術風格圖片結合創造出另一張具有藝術風格但內容卻是原來的圖片。近來神經風格已經被廣泛地使用在藝術教育和工業應用方面並產生各種風格，其視覺效果令人印象深刻。然而在神經風格化生成過程中，有三個原生問題需要注意。首先神經風格化圖片可能有過度風格化的現象，人們反而不喜歡。其次，預設內容/風格之權重可能不適用於某些風格，必須重新設置及訓練才能獲得滿意的效果。第三，由於神經網路本身結構的限制，通常會使得風格化圖片有低對比度之問題。本研究將提出一種基於影像融合、對比度增強與混合技術的快速後處理架構解決上述問題。為了驗證所提出的多功能平台，我們將以三個實驗驗證其效果。

關鍵詞：混合技術，Brovey 變換，深度學習，圖像融合，強度-色調-飽和度，神經風格轉換

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I . INTRODUCTION

Among deep learning techniques, the convolutional neural networks (CNN) have been validated to be quite useful for image analysis and applications. For examples, CNN-based art style transfers have recently been employed to produce impressive artwork [1-4] to such an extent that a new market has been created for the mobile apps that can stylize user-provided images with a particular art style. The popularity of commercial apps like Prisma [5] and Deepart.io [6] has been apparently increased. The task of the neural style transfer (NST) is to generate a stylized image S_C with the style of the image S and the content of the image C , respectively. The NST methods can be divided into two categories, namely the descriptive neural methods which are based on image iteration and the generative neural methods which are based on model iteration [7]. According to the development process, there are three major approaches in the descriptive neural method, that is, the original NST [1], the Fast Style Transfer (FST) [3], and the Multi-Style Transfer (MST) [4]. During the training phase in art education and industrial applications, the MST is advantageous to effectively and efficiently produce a variety of styles for the specified image.

Although the artistic effect of the NST-based methods is impressive, there are three issues worthy of noting. The first is the color of the S_C image will eventually become the color of the S image, i.e. the S_C image is over-stylized. It is usually undesirable for most artwork applications. In order to tackle this problem, one possible way is to use the luminance-only transfer [8] by a 3×3 kernel to convert the C and S images from the RGB color space to the YIQ space, respectively. In the inverse conversion, the I and Q components of the C image are retained and the Y component of the C image is replaced by that of the S_C image. Consequently, the color information of the C image can be preserved in the new image while the spatial details of the new image are inherited from the S_C image. Second, in the control of the trade-off between content and style in the S_C image, the predefined relative content-style weight plays a key role. If the stylized effect is not as expected, one solution is to use blending

technique to adjust the mixing ratio between C and S_C images [9]. Therefore, retraining is not required at all. The third concern is the use of batch or instance normalization in FST and MST. It is particularly useful for forward propagation when the number of CNN layers is too large. However, the normalization may significantly degrade the image contrast performance. To improve the visual effect, some effective contrast enhancing methods have been proposed [10]. It is noted that almost all the implementations of the proposed algorithms are segmentally. When the effect is not as expected, the style transfer procedures must be executed iteratively. In FST and MST, the style evaluation is very fast, and the most time-consuming operation is in the training phase. Since what most of the user concern is the style itself, not the style training. Thus, it will not be acceptable to spend too much time to enhance the S_C image. In addition to be effective, a good post-processing operation is also required to be fast and simple to use.

In this work, the image fusion algorithm can be applied to post-process the S_C images. This work proposes a versatile post-processing framework that combines Brovery transform (BT) [11], blending technique, and intensity conservation direct decorrelation stretch (ICDDS) [12] methods to tackle the above-mentioned three issues simultaneously. This framework composed of six modules is implemented by a window-based program which is used to demonstrate the adjustment of the S_C image. To validate the proposed techniques, three experiments are conducted with the stylized image produced from the MST method.

II . REVIEW OF THREE NST-BASED APPROACHES

The well-known NST is based on the article "A Neural Algorithm of Artistic Style" written by Gatys et al. [1]. In this paper, CNN is first proposed to learn art style transfer. By using a pre-trained VGG network, an S image is integrated into the C image to obtain a new S_C image. The purpose of this operation is to maintain the content of the C image for the S_C image while the unique styles of the S image, such as textures, tones, and strokes are embedded.

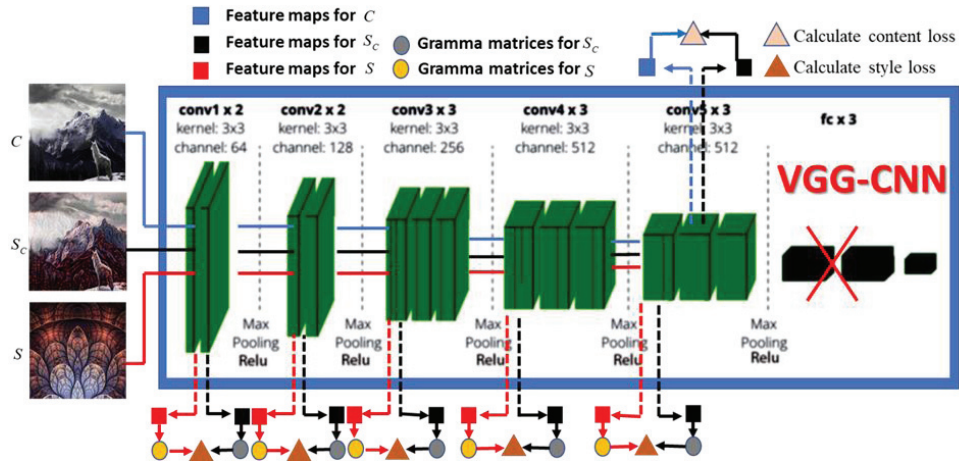


Fig. 1. The NST architecture

Fig. 1 shows the architecture of NST in which the core network VGG is a CNN trained for object recognition including a set of feature extraction layers and three fully connected layers for classification [13]. For NST applications, the three fully connected layers will be ignored and the steps of the optimization are as follows:

1. Synthesize a white noise image or directly use the original C as the initial S_C image.
2. Calculate the content loss by determining the distance between the C and S_C images in the high-level layer.
3. Calculates the gram matrix of the feature maps for the S and S_C images in each layer.
4. Calculate the style loss by determining the distance between the gram matrices of the S and S_C images.
5. The cost function is then defined by

$$L(C, S, S_C) = \alpha \cdot L(C, S_C) + \beta \cdot L(S, S_C) \quad (1)$$

where α and β are the weighting factors for content and style reconstruction, respectively. This loss formula can be used to evaluate the S_C image whether the style transfer is achieved.

6. Update the S_C by calculating the gradient of the cost function. If the gradient is not zero, one more iteration of the optimization is executed. It will generate a new S_C image which closer to the C content-wise and closer to S style-wise, respectively.
7. Steps from 2 to 6 are repeated until the preset number of iteration or the goal is reached.

Based on this procedure, high perceptual quality can be successfully obtained for the S_C image. However, it has to be indicated that retraining is required if the content or the style is changed since NST cannot save the mode of the trained style. Hence, it may not be suitable for real-time applications. Johnson et al. proposed the fast style transfer (FST) [3], which is possible to train a neural network by applying a single style to the content images with a single forward network. The architecture of the FST network shown in Fig. 2 consists of an image transform net (ITN) and a loss computing net. The ITN is a deep residual network that transforms an input C image to a corresponding output $\hat{C}$ image which should have the content of the C image and the style of the S image after the training. The original deep residual network has the batch normalization (BN) [14] layer in each CNN block, which is useful for forward propagation when the number of layers of CNN is too large. More recently, Ulyanov et al. have found a simple but more effective approach called Instance Normalization (IN) [15]. The IN is similar to the BN except it does not accumulate mean and variance. The loss network of FST is the same as the VGG-CNN originally used in NST, that is, the losses of style and content of $\hat{C}$ are obtained by calculating the distance between $\hat{C}$ and S in style, and $\hat{C}$ and C in content, respectively.

During the training phase, the style image is fixed and the Microsoft COCO dataset are chosen as different content images. The loss network is used to evaluate the loss and gradient of each

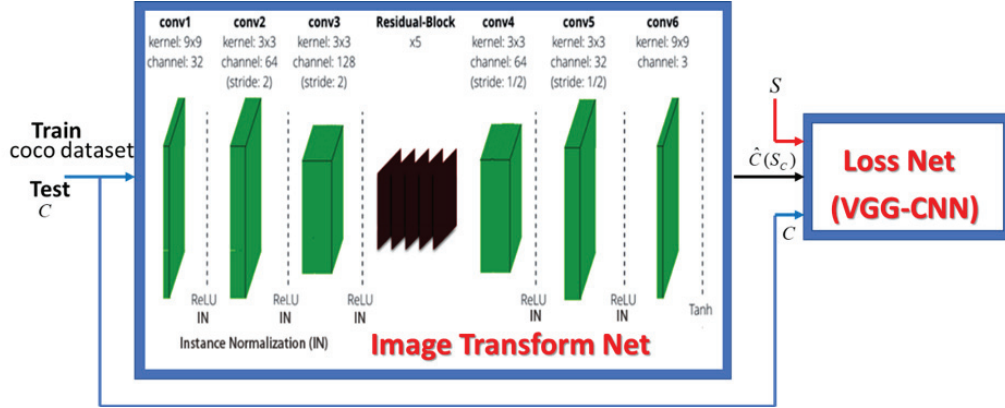


Fig. 2. The FST architecture

training sample, and the weights of each layer in ITN are then updated. After the training is finished, only ITN weights are required to generate the stylized images. The processing of FST is faster than NST, however, it is noted that a FST network is allowed to train only one style and not possible to mix multiple styles. To extend FST to multi-style transfer (MST), Dumoulin et al. at Google Brain have conducted an experimental work [4], showing that the distinction between the different styles of transfer operations is not reflected in the various convolution operations, but on the scale (γ) and shift (β) operations in the BN or the improved IN layers, which can be expressed as

$$z = \gamma \frac{x - \mu}{\sigma} + \beta \quad (2)$$

Thus, the parameters from different style of transfer models can be integrated into a specified model. Based on this finding, MST replace the IN layer with the conditional instance normalization (CIN) layer, i.e.

$$z_n = \gamma_n \frac{x - \mu}{\sigma} + \beta_n \quad (3)$$

where n is the number of style image. According to (3), a new style can be added by training a new set of gamma and beta. In addition, the style control weight (SCW) vector can be used in the mixing of different styles. For example:

If only Style 2 is specified, the instruction can be expressed as

Set -scw "0 1 0 ... 0 0 0".

If the weighting for Style 1 and 3 are 0.3 and 0.7, respectively, the instruction simply becomes as follow as

Set -scw "0.3 0 0.7 0 ... 0 0 0"

More detail information can be found in [16].

III. THE PROPOSED METHOD

The neural stylized effect is impressive, but it is limited in certain respects as described in Sec. I. Although the problems can be solved separately, it may be quite time-consuming and cumbersome. Aimed at finding an effective solution, the image fusion and the color enhancement by ICDDS technique used in remote sensing community are applied. In the following, BT and ICDDS methods will be briefly introduced.

3.1 Image fusion by BT

Among various image fusion methods, BT is frequently used. It can be represented as [11]

$$\begin{bmatrix} R_{BT} \\ G_{BT} \\ B_{BT} \end{bmatrix} = \frac{P}{I} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (4)$$

where $[R_{BT} \ G_{BT} \ B_{BT}]$ is the fused image by the BT method, $I = (R + G + B)/3$ is the intensity component of the low-resolution RGB image, and P is the high-resolution panchromatic image. Using BT to replace the luminance-only transfer is an effective method because it does not require coordinate conversion.

3.2 Color enhance by ICDDS

As mentioned in Sec. II, the S_C images produced by the FST or MST are usually less contrast. The remote sensing images also have the similar problem. The multispectral bands are often highly correlated and thus unable to be adequately shown on RGB displays by independent contrast stretching, which is caused

by the limit of sensor bandwidth. To solve this problem, the Intensity Conservation Direct Decorrelation Stretch (ICDDS) technique has been presented in [12]. ICDDS method is represented as

$$\begin{bmatrix} R' \\ G' \\ B' \end{bmatrix} = \frac{I}{I - k \cdot a} \begin{bmatrix} R - k \cdot a \\ G - k \cdot a \\ B - k \cdot a \end{bmatrix} \quad (5)$$

where $a = \min(R, G, B)$, k ranging from 0 to 1 is an adjustable parameter to control the degree of saturation stretch in the processed image.

3.3 The proposed method

In NST, the luminance-only transfer is often performed in YIQ or similar color models. However, using image fusion methods to replace the luminance-only transfer is quite straight-forward and effective. In order to facilitate the integration, this work uses the BT approach which can be represented as follows

$$\begin{bmatrix} R_{Sp} \\ G_{Sp} \\ B_{Sp} \end{bmatrix} = \frac{I_{SC}}{I_C} \cdot \begin{bmatrix} R_C \\ G_C \\ B_C \end{bmatrix} \quad (6)$$

where the $[R_{Sp} \ G_{Sp} \ B_{Sp}]^T$ is the style (color) preserved image, $I_{SC} = (R_{SC} + G_{SC} + B_{SC}) / 3$ and $I_C = (R_C + G_C + B_C) / 3$ are the intensity components of the S_C and C image, respectively. It is obvious that the S_P image has the same spatial details of the original S_C image while keeping the same hue information of the C image. Therefore, (6) fulfills the requirements of luminance-only transfer.

Furthermore, (6) can be directly integrated into (5) for ICDDS. That is

$$\begin{bmatrix} R'_{Sp} \\ G'_{Sp} \\ B'_{Sp} \end{bmatrix} = \frac{I_{SC}}{I_C - k \cdot a_c} \begin{bmatrix} R_C - k \cdot a_c \\ G_C - k \cdot a_c \\ B_C - k \cdot a_c \end{bmatrix} \quad (7)$$

where $[R'_{Sp} \ G'_{Sp} \ B'_{Sp}]^T$ is the S_C image with color enhance and $a_c = \min(R_C, G_C, B_C)$. As expected, the new S_P image has the same spatial details as the original S_C image while the color information can be efficiently enhanced.

To solve the second issue mentioned in the Sec. I, one can use the blending technique to re-adjust the mixing ratio between the C and S_C images. A possible approach is to integrate the

blending technique into (7) as shown below

$$\begin{bmatrix} R'_{Sp} \\ G'_{Sp} \\ B'_{Sp} \end{bmatrix} = \frac{k_1 \cdot I_C + (1 - k_1) I_{SC}}{I_C - k_2 \cdot a_c} \cdot \begin{bmatrix} R_C - k_2 \cdot a_c \\ G_C - k_2 \cdot a_c \\ B_C - k_2 \cdot a_c \end{bmatrix} \quad (8)$$

where the parameter k_1 ranging from 0 to 1 is for adjusting the blend ratio between the C and S_C images, k_2 ranging from -1 to 1 is for controlling the degree of saturation compression or stretch.

Different from (8), the function is style (color) preserved. Sometimes we may need the opposite operation to keep the spatial details of the C image and the enhanced color information in the S_C image. To build this function, (8) can be modified as

$$\begin{bmatrix} R'_{Cp} \\ G'_{Cp} \\ B'_{Cp} \end{bmatrix} = \frac{k_1 \cdot I_{SC} + (1 - k_1) I_C}{I_{SC} - k_2 \cdot a_{SC}} \cdot \begin{bmatrix} R_{SC} - k_2 \cdot a_{SC} \\ G_{SC} - k_2 \cdot a_{SC} \\ B_{SC} - k_2 \cdot a_{SC} \end{bmatrix} \quad (9)$$

where $[R'_{Cp} \ G'_{Cp} \ B'_{Cp}]^T$ is the content-preserved S_C image, and $a_{SC} = \min(R_{SC}, G_{SC}, B_{SC})$.

Based on (8) and (9), six different modules are (i) the content preserved module, (ii) the style preserved module, (iii) the style preserved module with the content/style blending, (iv) the content preserved module with the content/style blending, (v) The style preserved module with the content/style blending and the contrast adjusting, and (vi) the content preserved module with the content/style blending and the contrast adjusting. The two most important modules of the proposed approach are (v) and (vi). Modules (v) and (vi) can not only combine the spatial details of the style/content image with the color information of the content/style image, but also control the compression or stretch of image saturation. Thus, they can provide more visual-pleasing effects in the new stylized image which will be shown in the next section.

IV. EXPERIMENTAL RESULTS

The proposed versatile framework has been implemented by a window-based program, as shown in Fig. 3. Based on the concept of "What You See Is What You Get" (WYSIWYG), the window consists of five sub-windows which are called the Main window and four Thumbnail Previews, respectively. Initially, the S_C and C images are read and displayed on the upper left and upper right sides of the main window. Next,

select the content or the style preserved module and execute. The resultant C_P or S_P images will be displayed at the bottom left or bottom right side of the Main window. The default is the module (i), however, the user can easily change the module and adjust the parameters k_1 and k_2 to find the most satisfactory module. The processing results are real-time obtained and analyzed. In the following, three art style transfer experiments are conducted.

The first experiment demonstrates the operations and corresponding results of the proposed versatile framework. The C image is a digital painting image, and its S_C image is generated by the single style mode of the MST algorithm. The S_C , C , and the resultant C_P and S_P images are shown in Fig. 3, respectively. Compared to the S_C and C images, both the C_P and S_P images achieve their intended functionality. By the default settings in modules (i), we have $k_1 = k_2 = 0$. Thus, the C_P image can keep the spatial details of the C image and maintain the color information of the S_C image while the S_P image is the result of the opposite function provided by modules (ii). To evaluate modules (iii) and (iv), the parameter k_1 (B_{adj}) is set between 0 and 1 to obtain an image with different mixing effects. The C_P images with $k_1 = 0.2, 0.5$, and 0.8 from left to right in sequence are displayed on the upper row in Fig. 4. Bottom row is the S_P images with the same k_1 values as C_P . Compared to the original S_C and C images in Fig. 3, the style effect in the C_P images are increased gradually by increasing the k_1 value. On the contrary, the style effects in the S_P images are then decreased gradually. As expected, both modules (iii) and (iv) achieve the design goals, this allows the user to flexibly choose his favorite composition of the C and S_C images. In order to make the image contrast more variable, the modules (v) and (vi), extended from the modules (iii) and (iv), can perform contrast reduction or enhancement. First, set the value of k_1 (B_{adj}) by choosing a favorite type of mixing, and then adjust the k_2 (S_{adj}) value to control the required saturation. When $k_2 < 0$, the contrast is reduced, the smaller the k_2 is, the lower the contrast of the image. But when $k_2 > 0$, the effect is just the opposite, that is, the contrast is enhanced. The resultant images with different k_2 values are demonstrated in Fig. 5. The first row is displayed the reduced-contrast C_P images

with a fixed $k_1 = 0.5$ and $k_2 = -0.8, -0.5$, and -0.2 , from left to right in sequence. The second row shows the enhanced-contrast C_P with the same k_1 value, but $k_2 = 0.2, 0.5$, and 0.8 , respectively. The third and fourth rows are the contrast reduced and enhanced S_P images with the same k_1 and k_2 values as the first and second rows, respectively. As can be seen in Fig. 3, the saturation of each image has reached the desired effect. This demonstrates that the proposed method can execute the functions of replacement, mixing and contrast adjustment to improve the neural stylized image.

Artists often need to render different colors for sketches or monotonous textures which is time-consuming and tedious. In the second experiment, we will show that the style preserved module (v) is able to provide the color re-rendering effect. It is noted that the multi-style mode of MST during the training phase can produce multi-stylized images for style assessment. With the practical application of the MST and the proposed module (v), artist's rendering work will become straight-forward and enjoyable. For demonstration, ten S images are applied to train the MST to generate ten single-style and forty-five mixed-stylized images which are produced by mixing half of the two single style images. The C image and the total fifty-five S_C images are shown in Fig. 6. The C image on the upper left corner is the texture pattern while the others are the produced S_C images. As can be seen in Fig. 4, these S_C images show different rendering colors that can provide the diversity for art workers to choose. Although this re-coloring work has become easier by MST, these S_C images are not good enough. This is due to the fact that the S_C image produced by NST-based algorithms is usually over-stylized and less contrast. In this aspect, the adjustability of module (v) is convenient; this interesting result will be demonstrated in Fig. 7. The original C image is shown on the middle of the first row, three S_C images are displayed in the second row, and the three produced C_P images are demonstrated in the third row, in which $k_1 = 0$ and $k_2 = 0$ for module (v). In this case, the operation of module (v) is to use the spatial details of the C image to completely replace that of the S_C image, while the contrast of S_C image is intensively enhanced. Compared to the C and S_C images, the resultant C_P images have reached

the desired goal in terms of spatial detail and color information. It can be seen that these C_P images are beautiful and clear while the original

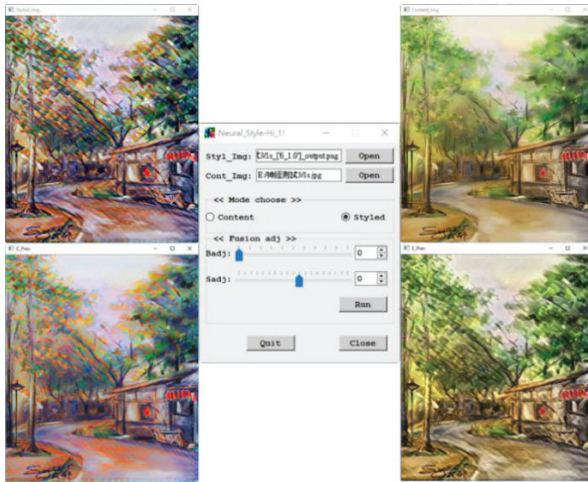


Fig. 3. Upper left: the S_C image, upper right: the C image, bottom left: the C_P image, bottom right: the S_P image, and middle: main window

S_C images are less contrast. Because the parameters are fixed, i.e. $k_I=0$ and



Fig. 4. Upper row: the mixed effects for the C_P images with $k_I=0.2, 0.5$, and 0.8 , from left to right. bottom row: the S_P images with $k_I=0.2, 0.5$, and 0.8

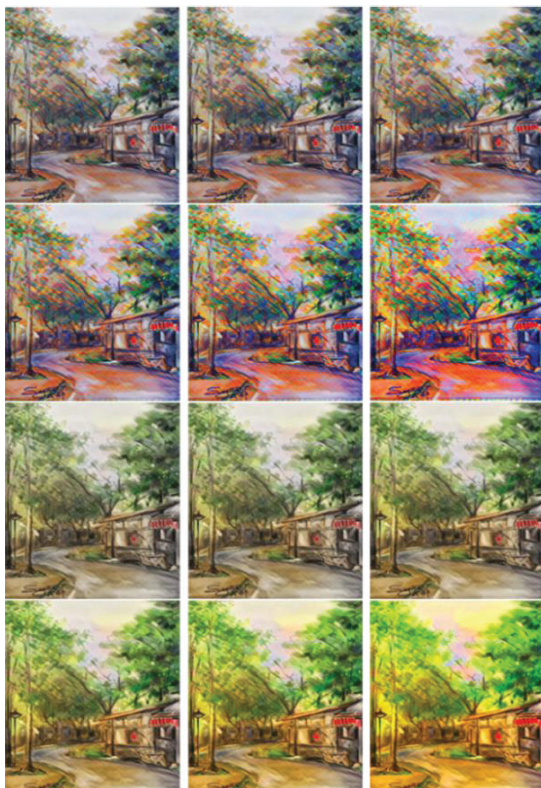


Fig 5. First row: the contrast reduced C_P images
Second row: the contrast enhanced C_P images
Third row: the contrast Reduced S_P images
Fourth row: the contrast Enhanced S_P images



Fig 6. The upper left corner is the C image, the others are the S_C images

$k_2=0.8$, module (v) can be executed by a batch operation so that this re-coloring work will be efficient.

The third experiment will show the results of a real digital painting processed by the MST and the proposed modules (v) and (vi). Fig. 8 shows the C , S_C , C_P , and S_P images are from top to bottom in sequence. The parameters are $k_1=0.4$, $k_2=0.2$ for module (v), and $k_1=0.5$, $k_2=-0.4$ for module (vi). As can be seen in Fig. 8, the original C image is simple and elegant, showing a relaxed and pleasant style. In contrast, the S_C image processed by the MST has a larger contrast in color and a clearly visible texture, showing a cool style. By using modules (v) and (vi), the C_P and S_P images are created by balancing the visual effects.

Also, it is not surprising that modules (v) and (vi) can also mix two different stylized images, that is, read another stylized image from the Main window instead of the C image. Fig. 9 shows images of S_{C1} , S_{C2} , C_P ($k_1=0.5$, $k_2=0.2$), and S_P ($k_1=0.5$, $k_2=-0.4$) from top to bottom. As can be seen in Fig. 9, the two stylized images S_{C1} and S_{C2} show their unique style. The S_{C1} image shows a refreshing style while the S_{C2} image displays a deep and quiet style. After adjustment, both C_P and S_P images show a relatively neutral style. By adjusting the saturation and embedding different texture styles, the modules (v) and (vi) can easily create a good special stylized image. More examples have also yielded similar results.

V. CONCLUSIONS

More recently, NST-based style transfer algorithms have demonstrated very exciting results that have attracted the academic and industry attention. In order to achieve more visual effects, researchers have been using more complex algorithms to improve CNN's learning or network architecture. However, the effect of these methods seems not satisfactory. Since the qualitative assessment is high subjective, there is no metric to evaluate artistic style transfer effects. In order to give users more choices, a versatile post-processing framework has been proposed in this work. In this framework, the blending technique, BT, and ICDDS methods have been fully integrated and implemented by a window-based program. It is easy to use and able to provide more visual effects for the stylized images. Especially in the second experiment, we provide art workers a good solution for process massive color rendering. It can provide users with more choices. When the deep learning technology is limited inherently, traditional methods like this work may sometimes be able to quickly solve the problem.

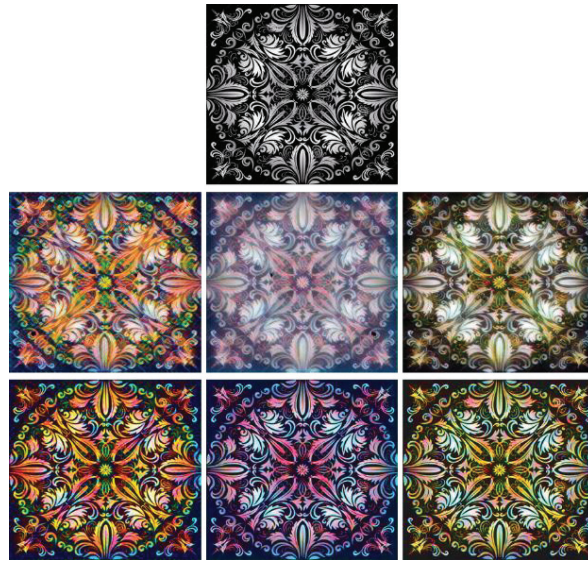


Fig 7. The middle of first row: the C Image, second row: three S_C images. third row: the three corresponding C_P images with $k_1=0$ and $k_2=0.8$



Fig. 8. From top to bottom: the C , S_C , $C_P(k_1=0.4, k_2=0.2)$, and $S_P(k_1=0.5, k_2=-0.4)$ images



Fig. 9. From top to bottom: the S_{C1} , S_{C2} , $C_P(k_1=0.5, k_2=0.2)$, and $S_P(k_1=0.5, k_2=-0.4)$ images

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