Adaptive Style Transfer Method of Art Works Based on Laplace Operator

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***Abstract*—In order to improve the image quality of artworks after style transfer, the adaptive style transfer method of artworks based on the Laplace operator is studied. Through three steps of expansion processing, corrosion processing and multi-scale morphological enhancement, the image edge of the content of artworks is enhanced. The colour and brightness of the artworks with edge enhancement are transferred, and the transfer results are input into the convolution neural network simultaneously with the style image. According to the improved Laplace operator, the Laplace operator loss term of the convolution neural system is counted, the style losing term of the style picture of the art image is determined, and the total loss function is constructed. According to the determined loss function, a convolution neural network is used to output paintings' adaptive style transfer results. The experiential outcomes indicate that this technique is able to realize the adaptive style transmission of paintings. After style transfer, the picture quality of paintings is high, and the adaptive transfer of artworks can be realized within 500ms.**

Keywords—Laplace operator; artworks; adaptive style transfer; brightness migration; convolution neural network

I. Introduction

With the development of computer technology, the task of image art creation can be accomplished excellently with the help of a computer's image processing ability. Convolution neural network is a powerful and effective model in image processing [1]. Deep learning is a heavyweight machine learning algorithm [2] with a huge hyperparametric space and requires strict computational efficiency in practical applications. To a large extent, it restricts the further promotion of the image style transfer method of deep learning in practical applications. Deep learning is still a black box inside, and the mathematical meaning of its hyperparametric space is still incomprehensible [3, 4]. The process of applying the style of one style image to another content image [5, 6] is an artistic creation and image editing technology. Deep learning has made great breakthroughs in computer vision in the fields of image processing, intelligent robots, natural language processing, data mining and unmanned driving. Image style transfer algorithm is an application of depth neural network [7]. The appearance of an image style transfer algorithm can make the generation of a master artist's painting become a reality in a short time.

At present, many researchers have carried out research on image migration methods. Yuchi et al. [8] performed K-means clustering matching on transition images and obtained the optimal energy equation for color transfer through two methods: hierarchical transfer and global transfer. This method can achieve effective color transfer of images, but after color transfer, the image quality is poor; Deng et al. [9] studied a tapestry based adaptive perceptual domain style transfer algorithm based on semantic segmentation, combining semantic segmentation tasks with adaptive perceptual domain style transfer algorithms, and proposing new content loss and style loss. Although this method can achieve effective image migration, there is a problem of unprotected content and image structure, and the results of graphic migration are not ideal; Sun et al. [10] proposed a local style transfer method based on residual neural networks. Generate an image that only completes style transfer for the target area through deconvolution. This method has high local style conversion ability and high execution efficiency, but there is a problem of losing the main structure of the content image, resulting in poor visual effect of stylized images.

In mathematics and physics, the Laplace operator is differential. The Laplace operator has many uses, and it is also an important example of an elliptic operator. The function that is zero by the Laplace operator is called a harmonic function; the Laplace operator is the core of Hodge's theory and is the result of De Rham's cohomology. Laplace operator can extract the edge information in the image, and emphasize the details and texture of the image. In the style transfer of art works, by performing Laplace filtering between the original image and a reference image with a specific style, the transferred image can retain the original content while maintaining the artistic style of the reference image. Therefore, in order to promote art creation and technology development, provide more possibilities for art creation, and apply the potential of this technology in different fields, research the adaptive style transfer method of art works based on Laplace operator. The motivation of using the Laplace operator for style transfer is that it can help artists achieve more accurate style conversion, making the transferred works more consistent with the expected artistic effect. The main ideas of this study are as follows:

1) Firstly, edge enhancement is performed on the content images of art works through dilation processing, corrosion processing, and multi-scale morphological enhancement algorithms.

2) After edge enhancement, Convolutional neural network is selected as the main framework of adaptive style transfer of art works.

3) The improved Laplace operator algorithm is studied, which combines Laplace operator with Convolutional neural network; then design an adaptive style migration network structure based on color, brightness and semantic information, and apply it to the adaptive style migration of art works to achieve migration.

4) Through experiments, it has been verified that this study can improve the transfer level of art works and obtain user satisfactory adaptive style transfer results.

II. MATERIALS AND METHODS

A. Edge Enhancement Algorithm of the Content Image of Artworks

1) Dilation processing: The expansion operator's task is to solve the maximum local value of the pixel in the artwork image. The structural element is used to calculate the area covered by the expansion operator in the artwork [11], find the maximum value of the pixel, and then input the calculated value into the element specified in the centre of the artwork structural element.

If $f(s,t)$ is the original artwork image, the artwork image after dilation processing is:

$$f_e(x,y) = (f \oplus b)(s,t) = \max\{f(s-x,t-y)+b(x,y)\} \quad (1)$$

In formula (1), b is a structural element; D_f and D_b are definition fields; $f \oplus b$ is the result of b dilating the original artwork image f

2) Corrosion processing: Contrary to the expansion operator, it is the task of the erosion operator to solve the local minimum value of pixels in the picture of paintings. The structural element is used to calculate the area of the artwork covered by the expansion operator, find out the minimum pixel value of each area of the corresponding artwork, and then input the calculated value into the element specified in the centre of the structural element. Corrosion processing is conducive to filtering noise [12], preserving the original information in the picture of paintings, making the edges smooth, and the extracted picture of paintings more continuous.

The picture of the artwork after corrosion processing is as follows:

$$f_c(x,y) = (f - b)(s,t) = \min\{f(s+x,t+y)-b(x,y)\} \quad (2)$$

In formula (2), $f - b$ is the result of corrosion operation on f

3) Multi-scale morphological enhancement algorithm: The selection of structural elements is very important to the edge detection results of artworks. Selecting only one structural element will result in discontinuous edge information of the detected artwork and generally cannot get a relatively complete edge contour of the artwork [13]. Using multi-scale structural elements can effectively solve the problem of edge discontinuity in artworks. Structural elements with different scales are used to calculate the image of artworks, and large-scale structural elements can effectively filter the image of artworks; Small-scale structural elements can be targeted to detect the contour of target features of artworks [14]. Two structural elements of different scales are combined to detect the edge of the image of the artwork.

The expression for defining multi-scale structure elements is as follows:

$$nB = B_1 \oplus B_2 \oplus \cdots \oplus B_n \quad (3)$$

In formula (3), n is the scale parameter; B is a structural element.

Using multi-scale and multi-structure element morphological edge detection operators, the expression for processing artworks is as follows:

$$f_B(x,y) = \frac{1}{2}\{\,[\,f_c(x,y)\Theta b_i(m,n) \oplus nB\,]\, \oplus f_e(x,y) \quad (4)$$

In formula (4), $f_B(x,y)$ is the image of artworks after multi-scale mathematical morphology processing; b_i is a structural element.

The circular structure element with the size of 3×3 and the rectangular structural element with the size of 6 ×2 are used as the structural element of the edge enhancement for the image of the artwork. The expression of the structural element is as follows:

$$b_1 = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} \quad (5)$$

$$b_2 = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 & 1 \end{bmatrix} \quad (6)$$

$$b_3 = \begin{bmatrix} 1 & 1 & 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 1 & 1 & 1 \end{bmatrix} \quad (7)$$

According to the structural element expression of formula (5) to (7), the circular structure element with the size of 3×3 is firstly used to expand and erode the image of the artwork. Then the rectangular structure element with the size of 6×2 is used to expand and erode the image of the work of art and complete the edge enhancement of the image of the artwork.

B. Style Transfer Network Structure of Convolution Neural Network

The convolution neural network is selected as the deep learning algorithm for the adaptive style transfer of artworks. A convolution neural network is a series of feedforward neural networks with depth, including convolution operation. Convolution neural network has strong learning ability because of their unique network structure [15]. Unlike the full connection strategy of traditional neural networks, each neuron of the convolution neural network is only connected with some neurons of other layers, and the parameters of the convolution kernel are shared, making the operation simple and efficient, and can learn on large data sets [16, 17]. A convolution neural network comprises the input layer, convolution layer, activation function [18], pooling layer [19] and full connection layer. Among them, the selection of the activation function in the activation layer greatly impacts the migration result of the adaptive style transmission of paintings. The ReLU function is selected as the activation function in the activation layer of the convolution neural system. The ReLU function is a function with the maximum value. The calculation formula of the ReLU function is as follows:

$$f(x)=\max(0,x) \tag{8}$$

The ReLU function mimics the biological neurons in the human brain and has the characteristics of dispersion and sparsity. The ReLU function is the most commonly used activation function at present. When the convolutional neural network uses the ReLU function as the activation function, there is no problem of gradient disappearing.

Maximum and average pooling are two common pooling ways of pooling layers in convolutional neural networks. The maximum pooling method is selected as the pooling operation of adaptive style migration of artworks. The full connection layer acts as a "classifier", mapping the learned features of artworks to the sample space. Full connection operation will cause a huge amount of parameters, so it is generally only used in the last few layers of the convolutional neural system to exploit the feature vectors of artworks to complete some classification tasks.

C. Laplace Operator and its Improvement

1) Laplace operator: The Laplace operator is an important algorithm in the adaptive style transfer processing of artworks. The Laplace operator is an edge point detection operator independent of an edge direction. It responds more strongly to isolated pixels in the picture of paintings than to edges or lines [20]. Before applying this operator to the adaptive style transmission of paintings, it needs to smooth the image of artworks. The Laplace operator is a second-order differential operator. Let the artwork image be a continuous, binary function $f(x,y)$, and its Laplace operation is defined as:

$$\nabla^2 f=\frac{\partial^2 f}{\partial x^2}+\frac{\partial^2 f}{\partial y^2} \tag{9}$$

The Laplacian operator of the image of artworks can be simplified as follows:

$$g(i,j)=4f(i,j)-f(i+1,j)-f(i-1,j)-f(i,j-1) \tag{10}$$

Formula (10) can also be expressed in the form of convolution, and the expression is as follows:

$$g(i,j)=\sum_{r=-k}^{k}\sum_{s=-t}^{l} f(i-r,j-s)H(r,s) \tag{11}$$

In formula (11), the sampling of $H(r,s)$ is as follows:

$$H_1=\begin{bmatrix}0 & -1 & 0\\ -1 & 0 & -1\\ 0 & -1 & 0\end{bmatrix} \tag{12}$$

In the process of adaptive style transmission of paintings, the Laplace operator of the function is realized with the help of templates. The effect of template sampling will directly affect the effect of adaptive style transfer of artworks.

2) Improved Laplace operator: The Gaussian function improves the Laplace operator, and the log operator represents the improved operator. The log operator is used to improve the application performance of the Laplace operator in the adaptive style transfer of artworks. The log operator is an improved operator based on the Laplace operator. The log operator first performs Gaussian convolution filtering on the artwork image to reduce noise [21], then uses the Laplace operator to detect the edge of the artwork image after noise reduction. The expression of the Gaussian convolution function $G(x,y)$ used to improve the Laplace operator is:

$$G(x,y)=\exp\left[-\frac{x^2+y^2}{2\sigma^2}\right]/2\pi\sigma^2 \tag{13}$$

In formula (13), x and y respectively represent the row coordinates and column coordinates of the pixel points of the artwork image; σ represents the standard deviation of pixels.

The original artwork image $f(x,y)$ is first convolved with the Gaussian function $G(x,y)$ to obtain the smoothed artwork image $g(x,y)$. The smoothed artwork image $g(x,y)$ is solved with the Laplace operator differential of the convolution. The expression of the operation process is as follows:

$$g(x,y)=G(x,y)\otimes f(x,y) \tag{14}$$

$$\nabla^2\left[f(x,y)\otimes G(x,y)\right]=f(x,y)\otimes\nabla^2 G(x,y) \tag{15}$$

$$\nabla^2 G(x,y)=\left(\frac{x^2+y^2-2\sigma^2}{2\sigma^2}\right)\exp\left(-\frac{\log\left(x^2+2y\right)^2}{2\sigma^2}\right) \tag{16}$$

In formula (14) to (16), $\otimes$ is a convolution symbol; ∇ is the differential sign; $\log$ is an improved Laplace operator.

Because the edge detected by the log operator is not very smooth and has a lot of noise [22], on the basis of using the operator detection, the two-dimensional digital filter is used again to filter and detect the image of the work of art. The detection process is as follows:

1) The filtered artwork image $y(n)$ can be expressed as:

$$y(n)=h(n)\times x(n)=\sum_{k=0}^{K-1}h(k)\times x(n-k) \tag{17}$$

In formula (17), $h(n)$ is the non-recursive filtering coefficient, $h(k)=\log(x,y)$; $x(n)$ is the input artwork image; K is the filter length, and the order is $K-1$. The coefficient matrix of the two-dimensional digital filter is rotated 180 ° to create a convolution kernel [23], and obtain the convolution kernel expression as follows:

$$H_i=\begin{bmatrix}0 & 1\\ 1 & 0\end{bmatrix}M_i \tag{18}$$

In formula (18), H_i is the convolution kernel created by rotating the filtering coefficient matrix of the two-dimensional digital filter by 180 °; M_i is the edge operator.

2) Two-dimensional convolution is used to realize the filtering operation of artwork images. The expression of the two-dimensional convolution operation of artwork images is:

$$C_i(s,t)=\sum_{m=0}^{M_r-1}\sum_{n=0}^{M_c-1}H_i(m,n)\otimes B(s-m,t-n) \tag{19}$$

In formula (19), $C_i(s,t)$ is the artwork image after filtering operation; M_r and M_c are the number of rows and columns of convolution kernel H_i, respectively; The number of rows and columns s and t of the picture of the artwork meet the requirements of $0\le s<M_r+N_r-1$, $0\le t<M_c+N_c-1$; N_r and N_c are the number of rows and columns of the input artwork image matrix B.

3) The filtered data of the artwork image are added, and the expression is:

$$S=\sum_{i=1}^{4}C_i(s,t)=\sum_{i=1}^{4}\sum_{m=0}^{M_r-1}\sum_{n=0}^{M_c-1}H_i(m,n)\otimes B(s-m,t-n) \tag{20}$$

In formula (20), S is the sum result of the filtered data of the artwork image.

Through the above process, the threshold segmentation of the artwork image is completed, and the edge contour information of the artwork image matrix B is obtained.

D. Adaptive Style Transfer of Artworks Based on Color and Brightness

In the stylized result graph of artworks, some of the generated results of the stylized transfer algorithm of the traditional neural network have color confusion, which affects the overall artistic effect of adaptive style transmission of paintings in visual effect. Inspired by the color migration algorithm in style migration [24], in the process of adaptive style transmission of paintings, the color details and brightness details of the content picture of paintings are retained by using the migration of color and brightness.

X_C represents content image, X_S represents style image, X_J represents after color matching and migration, $x_i=(R,G,B)^T$ represents the pixel color of the input artwork content image and the input artwork style image. The color matching of the content image X_C of the artwork is transferred to the style image X_S of the artwork, and gets the new artwork image X_J. Then, before and after the style transfer, the pixel value of the artwork image has the following mathematical mapping relationship:

$$x_{CJ}\leftarrow Ax_S+b \tag{21}$$

In formula (21), A represents a matrix of size of 3×3; b represents a vector of size of 3 ×1; x_S shows the pixel value of the input artwork style picture; x_{CJ} represents the pixel value change result of the artwork image after color style migration.

In order to obtain the pixel value x_{CJ} after color-matching migration when the painting style is transferred, the matrix A and vector b in formula (21) must be determined first. The color-matching migration process of artworks will be described in detail below.

μ_C and μ_S are defined to represent the mean value of each pixel of the input artwork content image and the input artwork style image in RGB color space; σ_C and σ_S represent the covariance of the input artwork content image and the input artwork style image, respectively. According to the definition of mean and covariance, it can get:

$$\begin{cases}\mu=\sum_i x_i/N\\ \sigma=\sum_i (x_i-\mu)(x_i-\mu)^T/N\end{cases} \tag{22}$$

After the color matching of the artwork content image X_C is transferred to the artwork style image X_S, when the new artwork image X_J is obtained, the pixel color mean value and pixel covariance of X_J must be consistent with the pixel color mean value and pixel covariance of X_C, that is, the existing expression is as follows:

$$\begin{cases} \mu_{C_J} = \mu_C \\ \sigma_{C_J} = \sigma_C \end{cases} \tag{23}$$

In formula (23), μ_{CJ} represents the mean value of X_J in the artwork image after color migration; σ_{CJ} represents the covariance of X_J of the artwork image after color migration.

According to the above formula, the mathematical relationship between matrix A and vector b can be obtained as follows:

$$\begin{cases} b = \mu_C - A\mu_S \\ A\sigma_S A^T = \sigma_C \end{cases} \tag{24}$$

According to the above formula and mathematical knowledge, the value of vector b is determined by matrix A. As long as matrix A is determined, vector b can be determined. From the knowledge of matrices, there are many matrices A that meet the above conditions. When solving matrix A, the image analogy method is used. The eigenvalue expression of the decomposition covariance matrix is as follows:

$$\sigma = UAU^T \tag{25}$$

The square root expression of matrix A can be obtained by calculating formula (25) as follows:

$$\sqrt{\sigma} = U\sqrt{A}U^T \tag{26}$$

The expression for obtaining the value of matrix A through formula transformation is as follows:

$$A = 1/\sqrt{\sigma_C}\sqrt{\sigma_S} \tag{27}$$

According to the above mathematical ideas, the color of the content image of the artwork is successfully matched and transferred to the style picture of the painting to avoid the loss of the traditional style transfer method. In the Lab color space of the artwork image, the color value of each pixel is separated into one brightness channel, L and two color channels, a and b, which provide conditions for the color brightness separation of the artwork image's adaptive style migration [25]. The brightness of the content image of the artworks and the brightness of the style image of the artworks are extracted separately in the Lab color space. The brightness information of the content picture of the paintings is transferred to the style image of the paintings so as to match the brightness information of the content image of the artworks with the brightness information of the style picture of the paintings and achieve the purpose of preserving the color of the content picture of the paintings [26], so as to improve the problem of color mixing in the resulting image obtained from the style transmission of paintings.

H_C and H_S represent the brightness channel of the content image and style image of the artworks; H_J refers to the brightness pixel of the style picture of the paintings after the brightness migration; B_C and B_S show the medium brightness of the content picture and the style picture of the paintings; d_C and d_S represent the standard deviation between the content image of the work of art and the style image of the work of art, then the brightness transfer from the content image of the work of art to the style image of the work of art can be expressed as follows:

$$H_J = d_C\left(H_S - B_S\right)/d_S + B_C \tag{28}$$

Through the above process, it can complete the color and brightness transfer process of an artwork's image's adaptive style transfer and improve the level of the artworks image's adaptive style transfer through the color and brightness transfer of the artwork's image.

E. Self-Adaptive Style Transmission of Paintings on the Basis of Semantic Information

1) Determination of loss function: In the process of adaptive style transmission of paintings, to restrict the image transfer of artworks without redundant semantic information, based on the Laplace operator and convolution neural network method, the semantic information transmission of adaptive style transfer of paintings is realized by using Laplace operator to enhance the semantic information method. The method of the Laplacian operator to enhance semantic information increases the deeper information in the convolutional neural system and fully considers the loss of style transmission of artworks. A grim matrix is used to construct the style transfer loss of the convolutional neural network.

The content loss expression of the convolutional neural system for adaptive style transfer is as follows:

$$L_c = L_{lap} + \gamma L_{r_1} + \delta L_{r_2} \tag{29}$$

In formula (29), L_c represents the losing function of the content picture of the artwork, L_{lap} represents the loss function of the Laplace operator, L_{r_1} and L_{r_2} represent the adjustment coefficient of the loss function, and δ and γ are the weights of the latter two loss function terms. In order to prevent the network from over-fitting due to excessive loss during the training of the convolutional neural network, which affects the final generalization effect, both δ and γ are set to 0.5.

The original artwork image P_c and the migrated artwork image P_o are input into the loss network to calculate the mean square loss of the artwork adaptive style transfer so that the forward propagation error of the convolution neural network can be corrected. The structure diagram of the content loss network of the artwork image is shown in Fig. 1.

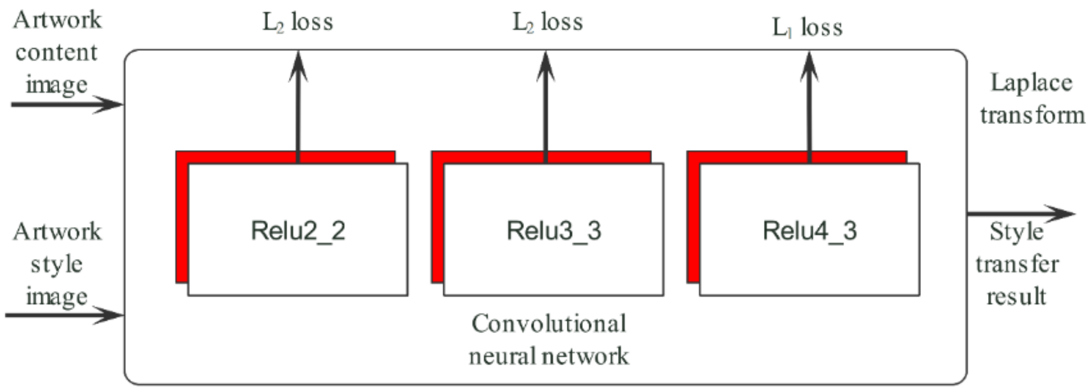


Fig. 1. Graphic content loss network structure of artworks.

In Fig 1, the improved Laplace operator log operator is used to perform the Laplace transform of the artwork image. The loss function L_{lap} of the Laplace operator is calculated as follows:

$$L_{lap} = \frac{C_{l_c}}{W_{l_c} L_{l_c}} \sum_{ij} \left\| lap\left(F_l\left(P_c\right)\right) - lap\left(F_l\left(P_o\right)\right) \right\|_{ij} \tag{30}$$

In formula (30), the value of l_c is Relu4_ 3. The Laplace operator used in the loss function is the improved Laplace operator log operator. P_c is input into the network to output Relu4_ 3. The Laplace operator is used to filter; P_o repeats the above steps. L_1 error is performed by backpropagation to correct the error. The reason for using L_1 error is that L_1 has fewer constraints on the solution, so L_1 error has a better generalization effect than L_2 error.

Using the Laplace operator as the loss function that emphasizes the feature extraction of the convolution neural network will not modify the original artwork image with the Laplace operator, so adding this loss item will not affect the actual quality of the artwork image after style transfer. In the last two terms of the loss function, the Relu2_ 2 and Relu3_ 3 of the convolution neural network are the standards to judge the loss of the content of artworks. The deeper features of the artwork can be obtained using the deeper convolution neural network output. Suppose the deeper image features of the original artwork are consistent with the image features of the artwork after style transfer. In that case, the artwork's image features better constrain the original image's semantic content. After adaptive style transfer, the image of the artwork will be closer to the original artwork image to constrain the artefacts unrelated to the original artwork's image semantics due to style transfer.

The calculation method of L_{r_1} in formula (29) is as follows:

$$L_{r_1} = \frac{C_{l_c}}{W_{l_c} L_{l_c}} \sum_{i,j} \left\| F_l\left(P_c\right) - F_l\left(P_o\right) \right\|_{ij}^2 \tag{31}$$

The calculation method of L_{r_2} is the same as that of L_{r_1}. The only difference between the two is that the value of l_c and is Relu2_ 2 and Relu3_ 3, respectively.

2) Structure design of adaptive style migration network: The overall structure of the adaptive style transfer method of artworks based on the Laplace operator is shown in Fig. 2.

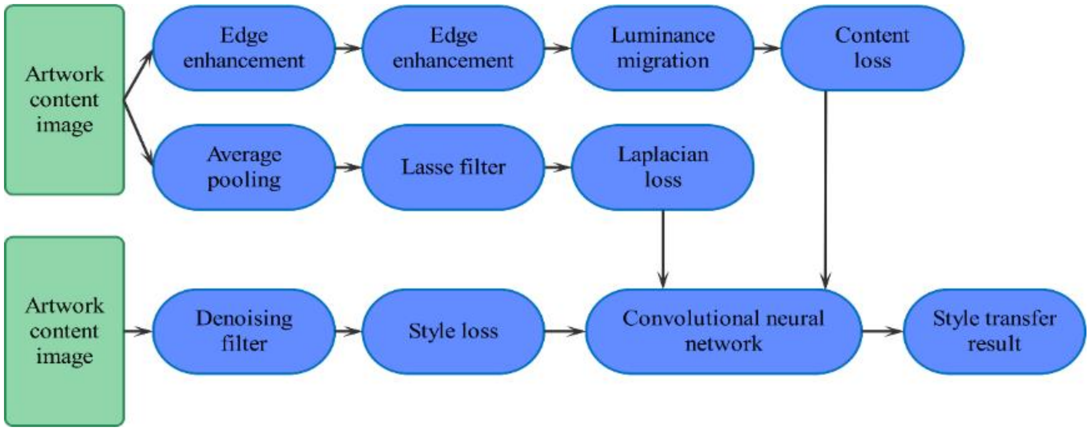


Fig. 2. Adaptive style transfer structure diagram.

It can be seen from the structure chart of adaptive style transfer of artworks in Fig. 2 that the Laplace loss term between the content image of paintings and the stylized picture of paintings is taken as the control dimension of the stylized detail feature of artworks image and added to the total loss function of adaptive style transfer. At the same time, the impact of the color brightness information of the content image and style image on the stylized visual effect is comprehensively considered. Detailed analysis of the specific implementation steps of adaptive style transfer of artworks images is as follows:

1) Input the artwork content image and artwork style image and carry out edge enhancement processing on them; during the edge enhancement process, effectively filter the noise in the artwork image and reduce the impact of the noise in the artwork image on the subsequent adaptive style migration process and the calculation of each loss item.

2) Convert the content image and style image of the artwork from RGB space to Lab space, realize the separation of image brightness channel L and colour channels a and b, transfer the brightness information of the content image of the artwork to the style image of the artwork, and retain the colour information of the content image of the artwork.

3) Input the content image of the artwork after the brightness transfer and the initial stylized result map into the convolution neural network, and carry out the statistics of the content loss items of the convolution neural system to obtain the loss function of the content picture of the artwork.

4) Make statistics of Laplace operator loss term of convolution neural network.

5) Evaluate the style losing function of the style picture of the art picture after denoising.

6) Construct a new total loss function and optimize iteratively in the convolution neural network; use the gradient descent method for continuous iteration of the convolution neural system; and output the adaptive style transfer result chart of paintings. In the process of style transmission of paintings, all loss items are calculated simultaneously.

III. Results

In order to verify the adaptive style transfer method of artworks based on the Laplace operator and the effectiveness of adaptive style transmission of paintings, the paintings collection in the network is selected as the test set, which contains 254 artworks in total. The artworks collection is divided into the content of the artworks set and the artworks style set, which contain 185 images and 69 images, respectively. The method in this paper is programmed by Matlab software, which is run to test the adaptive style transfer of the test set of artworks.

In this paper, a convolution neural network is used as the method of adaptive style transmission of paintings. The ReLU function is selected as the activation function of the convolution neural network. The curve of the ReLU function is shown in Fig. 3.

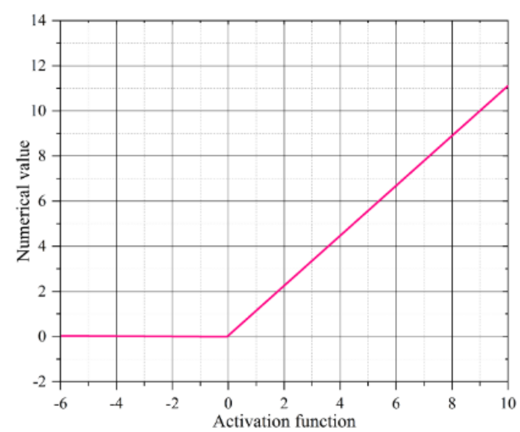


Fig. 3. Schematic diagram of ReLU activation function curve.

The method in this paper is used for adaptive style transmission of paintings. The loss curve changes during the operation of the method are shown in Fig. 4. At the same time, in order to verify the effectiveness of the proposed method, the residual neural network method in the same method reference [10] and the original Convolutional neural network are selected as the comparison method, and the loss curve is generated at the same time.

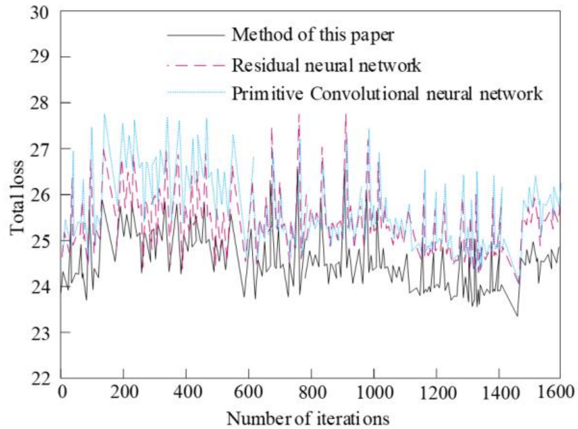


Fig. 4. Loss curve analysis.

A content picture of artwork is selected from the content set of the artwork test set. The content image of the original artwork is shown in Fig. 5.

Fig. 5. Original artwork content image.

Two artworks style images are selected from the content set of the artworks test set. The style image of the original artwork is shown in Fig. 6.

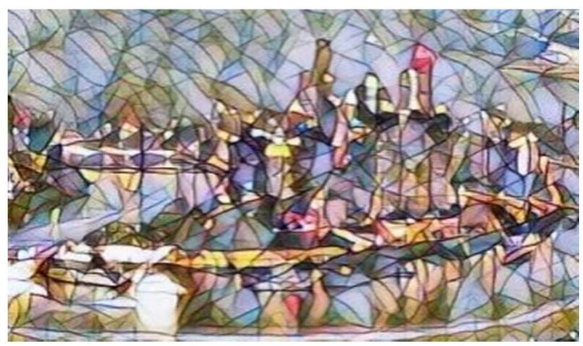
(a) Style image one.

(b) Style image 2.

Fig. 6. Original art style image.

The method in this paper uses the Laplace operator to conduct adaptive style transmission for paintings. The results of adaptive style transfer are shown in Fig. 7.

(a) Style transfer result I.



(b) Style transfer result II.

Fig. 7. Results of adaptive style transfer of artworks.

In order to further verify the adaptive style transfer performance of the method in this paper for artworks, the structural similarity index is selected as a measure of the structural similarity of artworks before and after style transfer. In order to verify the consistency of the structure of the artwork image and the original artwork image after the adaptive style transfer, structural similarity is used to determine the similarity between the two images. The calculation formula of structural similarity is as follows:

$$SSIM(x,y) = l(x,y)c(x,y)s(x,y) \tag{32}$$

In formula (32), $l(x,y)$ is the brightness estimation, $c(x,y)$ is the contrast estimation, and $s(x,y)$ is the structure estimation. The method in this paper is used to conduct adaptive style transfer for artworks. The statistical results of structural similarity are shown in Fig. 8.

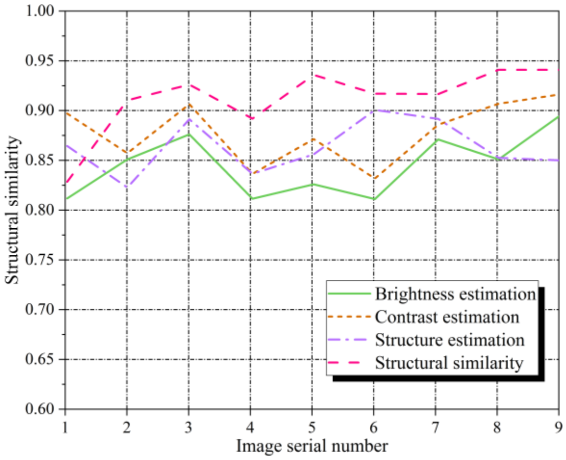


Fig. 8. Statistical results of structural similarity.

Stylization is an art editing work, and the quality of artistic works varies from person to person, so evaluating the quality of stylized images is a very subjective task. As scientific research, the image adaptive style transfer method should have rigorous and quantifiable evaluation indicators. The method in this paper is used to conduct adaptive style migration of artworks. The peak signal-to-noise ratio and migration time of style migration results are shown in Table I.

TABLE I. PERFORMANCE TEST RESULTS OF ADAPTIVE STYLE MIGRATION

Content image number	Style image number	Style transfer result	
		Peak signal-to-noise ratio /dB	Migration time /ms
1	A	35.6	354
2	A	33.4	285
3	A	31.5	415
4	B	32.8	365
5	B	34.5	385
6	B	32.9	346
7	C	31.5	456
8	C	33.7	395
9	C	34.5	405

IV. DISCUSSION

It can be seen from Fig. 3 that when the ReLU activation function inputs a negative value, the output result is 0, which means that only some neurons are activated at the same time, which makes the convolutional neural network more sparse. When this method is used for adaptive style transmission of paintings, the convolution neural network is set up, and the ReLU function is used as the activation function. When the adaptive style transfer of artworks, there is no problem of gradient disappearing. The convergence speed is fast, the calculation is simple, and the efficiency is high, effectively improving the effectiveness of the adaptive style transfer of artworks.

From the experimental results in Fig. 4, it can be seen that the total loss of this method in adaptive style transfer of art works is relatively low. The total loss of the residual neural network method in reference [10] is relatively high, and the total loss of the original Convolutional neural network is the highest among the three methods. This proves that the introduction of Loss function and Laplace operator in the process of adaptive style transfer of art works in this method reduces the loss in the process of adaptive style transfer of art works, and improves the style transfer performance of art works. The experimental results in Fig. 4 show that the adaptive style transfer of artworks using the method in this paper can improve the visual quality of the adaptive style transmission results of paintings and have better performance of minimizing the loss function.

From the experimental results in Fig. 7, we can see that using the method in this paper can achieve adaptive style transmission of paintings. The migrated paintings effectively retain the content of the original artworks content image and the style of the artworks style image. The artworks after style transfer can meet the user's adaptive style transfer needs. This method can achieve style transmission of paintings for different styles, and the effectiveness of style transfer is high.

As an art editing work, evaluating the style transmission effect of paintings is a highly subjective task. In addition to ensuring that the subject information is prominent, detailed information is also an important standard to measure the quality of a good work of art. In addition to preserving the prominent areas in the content image of the artwork, the contour information and line information of the objects in the content image should also be depicted in the stylized image. The method in this paper is used for adaptive style transmission of paintings, and its structural similarity is higher than 0.8. It is verified that the method in this paper can carefully constrain the detailed information of objects in the content image and stylized image, making the generated stylized image lines clearer and the visual effect more refined. This method achieves a balance between the preservation of image structure and the transfer of style elements, so the effect of style transfer is good.

The experimental results in Table I show that the peak signal-to-noise ratio is higher than 30 dB, the image quality is higher, and the style transfer time is less than 500 ms. From the perspective of the quality and time of style transfer image, the method in this paper has a high speed of style transfer, a high quality of style transfer, and a stable effect of style transfer, which can better balance the style and content of artworks. The content and style boundary of the composite image is clear, and the picture effect is good. The quality of the synthesized image is very high, which improves the clarity of the image's content structure and the style's expression ability. The 500ms migration time achieves the real-time migration effect without affecting the user experience of style migration. This method achieves a balance between style transfer time and image quality and achieves real-time high-quality style transfer effect.

V. CONCLUSION

As an excellent neural network in deep learning, convolution neural network has achieved remarkable results in target detection, classification and recognition, especially in image style transfer. Therefore, this article offers an adaptive style transmission method for paintings on the basis of the

Laplace operator. The combination of the Laplace operator and convolution neural network can better retain the semantic information of the content image in the stylized image and improve the visual effect of the stylized image. The experimental results show that the proposed method can obtain ideal style transfer results on the premise of ensuring the quality of style transfer images. The visual effect of style transfer is largely subjective, so the next step will be to add more objective experiments to verify the effectiveness and practicality of the method.

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