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Color Analysis of Cloud Brocade Pattern by Image Style Transfer

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Abstract

With the continuous improvement of the level of science and technology, the design method of cloud brocade pattern has gradually changed from the traditional process of color halo, white, and gold stranding to the modern design process, such as the synthesis of cloud brocade line pattern based on the transfer of image style. But back to reality, this method still has problems such as blurred outline and mixed colors, which is not conducive to the transfer of cloud brocade style pictures. Based on this, the paper will use the cloud brocade pattern style transfer color optimization model to analyze the color of the cloud brocade pattern in order to get a better cloud brocade style effect map. The results show that the average similarity of the local migration algorithm is 0.348, while the average similarity of the local migration algorithm based on color optimization is 0.378, which is 8.62% higher than that of the local migration algorithm. After 1600 iterations, the average running time of the local migration algorithm is 13.65s, and the running time of the local migration algorithm for color optimization is 12.46s. It can be seen that the local migration algorithm based on color optimization has obvious advantages in both comprehensive similarity and running time and can provide new ideas and references for the current design of Yunjin pictures.

Keywords: Style Transfer; Cloud Brocade Pattern; Color Optimization.

1. Introduction

As one of the three famous scenic spots in China, Yunjin has not only gained the favor of the general public due to its exquisite patterns, rich color matching, and fine weaving, but it also means that the traditional silk manufacturing process in China has reached a high level. For example, domestic scholars such as Liu et al. (2023) explored the inheritance and promotion path of Nanjing Yunjin based on the Internet and found that Nanjing Yunjin seized the opportunities of historical development and combined its own advantages. Integrating into the development of the new era has given rise to new vitality and provided many reference experiences for the development of intangible cultural heritage [1, 2].

In order to present the effect of different colors per flower, there are usually dozens of colors in the cloud brocade pattern. Traditional weaving craftsmen usually use techniques such as color halo formulas, alternating white and large, and gold twisted edges to match the pattern and complete the pattern design. For example, domestic scholar Pan (2023) took Nanjing cloud brocade as an example to explore and practice the cultivation of its intangible cultural heritage inheritors. We have gradually built a comprehensive education system for intangible cultural heritage inheritance based on "intangible cultural heritage inheritance+information technology+core literacy", integrating master inheritance and information technology, strengthening students' core literacy, practical skills, and innovation and entrepreneurship abilities, and achieving some results [3, 4].

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The traditional design method of cloud brocade pattern takes a long time, has low efficiency, and is affected by the skill level of the process inheritor, which greatly limits the innovative design of cloud brocade pattern and the activation and inheritance of products. With the development of image technology and artificial intelligence, image style transfer has been gradually applied to the fields of arts and crafts such as porcelain, lacquer, and painting [5, 6].

As a pattern design feature of Yunjin, it is also very suitable for using the method of image style transfer to complete the design. Style transfer refers to the process of re-rendering an image with the texture, color, and other styles of another image while keeping the content of the image unchanged. The current mainstream image style transfer method is based on a convolutional neural network algorithm, which extracts the image content and style from the content map and style map with the help of a training network and obtains the effect map through image reconstruction [7, 8].

The Yun brocade pattern is rich in color, and the effect drawing generated by the original style transfer algorithm is prone to problems such as color mixing. The outline of the target pattern and the content are unclear, so the design effect is poor. In order to inherit and innovate the design and application of cloud brocade based on the characteristics of cloud brocade patterns and the original transfer model, this paper proposes a local style transfer method based on color optimization. First, the mask of the target pattern is obtained to distinguish the pattern from the background, and the outline of the pattern is clear. Secondly, the variance sum of the composite image pixels in the three color channels is taken as the color loss in the total loss, and the color difference within the pattern is reduced by optimizing the color loss, and the semantic clarity of the pattern is improved. By combining color loss and mask mapping, the effect map of Yunjin style transfer with a clear outline and easy semantic recognition is obtained.

2. Principle of Image Style Transfer

The Visual Geometry Group (VGG19) model based on a convolutional neural network has 16 hidden layers (divided into 5 stages) and 3 fully connected layers, which have powerful image features and semantic expression ability [9, 10]. The original style transfer algorithm uses the VGG19 model to extract the underlying texture and high-level semantic information of the image as style and content, respectively, uses the optimization function to minimize the loss, and then iteratively updates the composite image to obtain the stylized effect diagram. The specific process is shown in Figure 1.

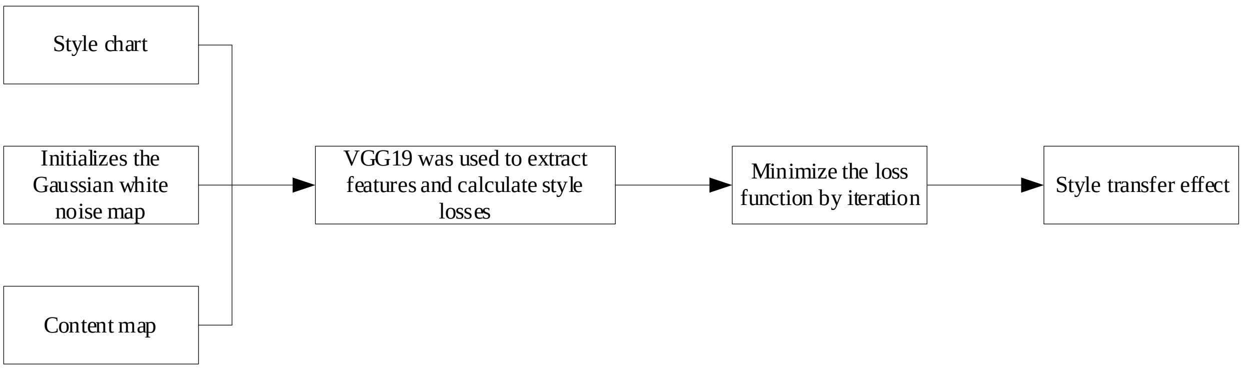

Figure 1. Process of image style transfer

Since the high-level convolutional network focuses on preserving the contour, semantic content, and other information of the image, the feature matrix of the content graph C and the composite graph G in the fourth layer of the convolutional neural network is selected, and the square error of the two feature matrices is the content loss, as shown in Equation 1.

$$L_{contet} = \frac{1}{2}\sum\nolimits_{l\in\{l_{content}\}} \left\| a^{[l]}(C) - a^{[l]}(G) \right\|^2 \tag{1}$$

Where, $a^{[l]}$ is the activation value matrix obtained by convolution of image I at the first layer [11], and its size is $n_C^{[l]} \times n_H^{[l]} \times n_W^{[l]}$. In terms of style, Gram matrix can describe the correlation between features by calculating the eccentric covariance matrix between features, such as the intensity of a feature, positive correlation or negative correlation between features, and so on, so as to obtain the style features of images. Transform $a^{[I]}(I)$ into a matrix of $n_C^{[I]} \times n_H^{[I]} \times n_W^{[I]}$, denoted as$a^{[I]}(I)^{`}$, then the Gram matrix I of the image G(I) is shown in Equation 2.

$$\mathrm{G(I)} = \frac{[a^{[I]}(I)^{`}][a^{[I]}(I)^{`}]^{\mathrm{T}}}{\mathrm{n}_\mathrm{C}^{[\mathrm{I}]} \times \mathrm{n}_\mathrm{H}^{[\mathrm{I}]} \times \mathrm{n}_\mathrm{W}^{[\mathrm{I}]}} \tag{2}$$

The Gram matrix of style graph S and composite graph G are calculated separately, and their square variances are denoted as style losses. Since the features extracted by the deep and shallow layer networks are different, in order to comprehensively summarize the image style features, the style loss of all the subsampled layers is calculated and recorded as the style loss, as shown in Equation 3.

$$L_{style} = \sum_{l\in\{l_{style}\}} \frac{1}{2} \|G(S) - G(G)\|^2 \tag{3}$$

In order to ensure the controllability of the composite image, content and style loss weights α and β are set respectively to adjust the style transfer effect, so the total loss is shown in Equation 4.

$$L_{total} = \alpha L_{content} + \beta L_{style} \tag{4}$$

3. Yun Brocade Pattern Style Transfer Color Optimization Model

In order to improve the problems such as color clutter, front and back scenes mixing, and unclear pattern outline in the migration effect diagram of Yun brocade lines, the paper added color loss and mask map on the basis of the original style transfer model and proposed a color optimization model of style transfer of Yun brocade patterns [12–14]. The structure of the model is shown in Figure 2.

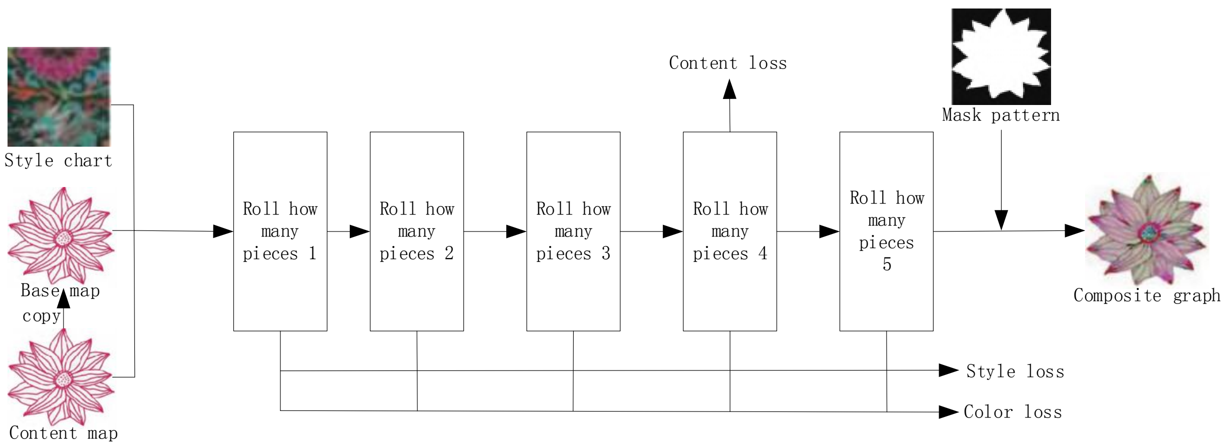

Figure 2. Color optimization model of Yunjin pattern style transfer

According to the structure of the color optimization model of Yunjin pattern style transfer, it can be seen that, first, the mask map of the content map can be obtained as the input with the help of the quick selection tool, and the content map can be copied as the base map. The Yunjin style map, line draft content map and base map can be respectively input into the VGG19 network after the pre-training, and the feature matrix can be extracted through convolution. Secondly, the content loss is calculated by the feature matrix of the content map and the base map. Calculate the color loss by using the base color map pixels; The synthesized base map is divided into three color channels R, G and B, and all pixels of the base map are traversed in each channel, denoted as Roi_{pn}. Each layer synthesizes the pixel variance andcolor loss in the three-channel base map. Since color belongs to the underlying texture information, the composite base map with the same number of layers is used for color loss and style loss (a total of 5 layers), and the specific calculation formula is shown in Equation 5.

$$L_{color} = \sum\nolimits_{l\in\left\{l\in\{l_{style}\}\right\}} \sum\nolimits_{c\in\{R、G、B\}} \frac{\sum_n \left(Roi_{pn}^{[c]} - \overline{Roi_{pn}^{[c]}}\right)^2}{n} \tag{5}$$

The total loss is the weighted sum of content loss, style loss, and color loss, as shown in Equation 6.

$$L_{total} = \alpha L_{content} + \beta L_{style} + \gamma L_{color} \tag{6}$$

In Formula 6, α, β and γ are the weights corresponding to the losses respectively, which can be adjusted according to the style needs. Finally, the Adam optimizer is selected to optimize the total loss, feedback and update the pixels of the base image to ensure that the iteratively generated base image is closer to the style of Yunjin image while retaining the original content, and the color difference of the composite image is minimized. Then combined with the mask map, output the cloud brocade style effect map with relatively clear contour and pattern semantics.

4. Experiment on Color Optimization of Yunjin Pattern by Image Style Transfer

Before carrying out the experiment of color optimization of cloud brocade pattern, it is necessary to make full preparation. Specifically, the Style migration optimization experiment was conducted using the Pytorch framework on a desktop with an Intel(R)core(TM)i7-117002.5GHz processor, NVIDIA GeForce RTX 3080Ti graphics card, and 32GB of RAM[15]. The Yunjin sample is used as the style diagram, and the line pattern is used as the content diagram. Since the migration model does not limit the image size, the experiment sets the size of the style map and the content map to 224*224 pixels, 300*300 pixels, 400*400 pixels, 512*512 pixels for comparison, and achieves the migration effect as shown in Figure 3.

Figure 3. Effect of pixel migration with different specifications

When the size is set to 224*224 pixels, the obvious migration effect can be obtained directly, and the consumption time is shortest. Considering the quality and processing time of the effect image, the size of the style image, content image and mask image is set to 224*224 pixels, and the size setting can be adjusted according to the size and clarity of the original image. Adam was selected as the model optimizer, and the learning rate was set to 5*10-3. The experimental results show that the absolute values of content loss, style loss and color loss are quite different. In order to balance the various losses, the three losses were balanced by using the coefficient, and the loss values were 1*10-3, 5*105 and 1*102, respectively, and the loss values were in the similar scale range, and the migration effect was good. In order to determine the number of iterations, the experiment selected three Yunjin style diagrams and line drawings as objects, set the initial iteration number of the optimization model to 2000, and output the loss value of content, style and color once every 100 iterations. The loss trend drawn is shown in Figure 4.

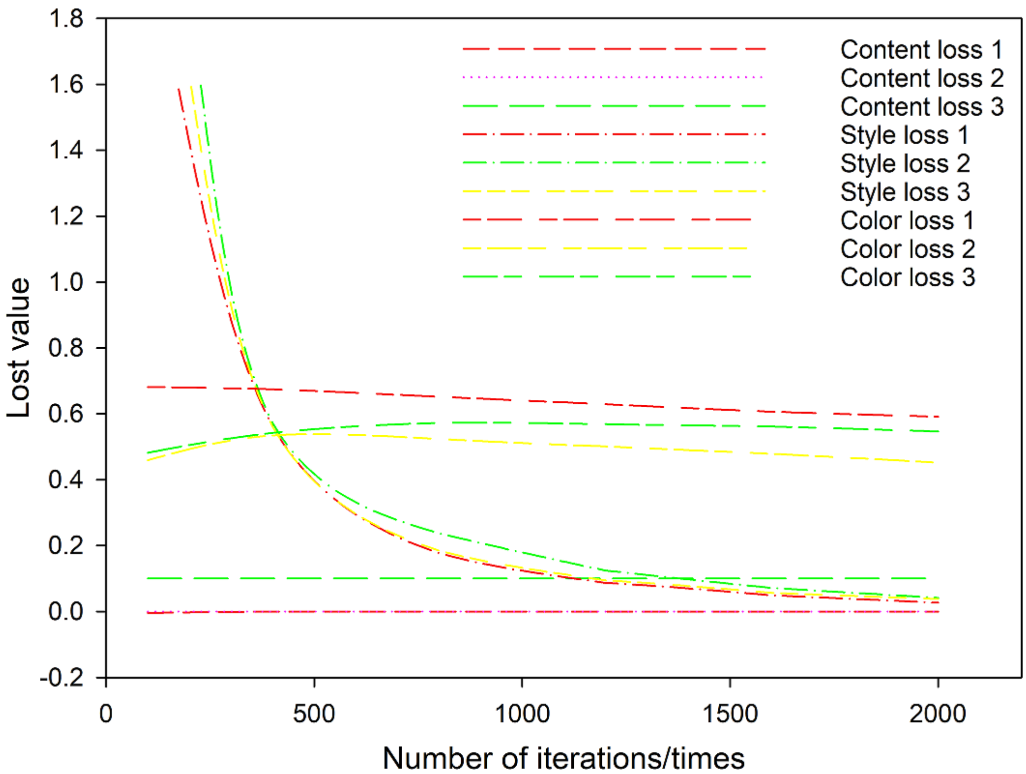

Figure 4. Content, style, color loss trend

It can be seen that the content loss hardly changes, and the style loss gradually decreases to a stable level with the increase of the number of iterations. As the style loss decreases, the style of the base map is closer and closer to the style of the style map, and the color is more complex, so the color loss presents a small value and then decreases to a stable trend. Combining the loss trend and training time, the experiment selects the synthesis graph of 1600 iterations to transfer the output graph.

4.1. Determination of Style Transfer Output Diagram

Based on the above basic Settings, the color optimization local migration algorithm proposed in this paper is compared with the original migration algorithm and local migration algorithm, and the resulting style migration output diagram is shown in Figure 5.

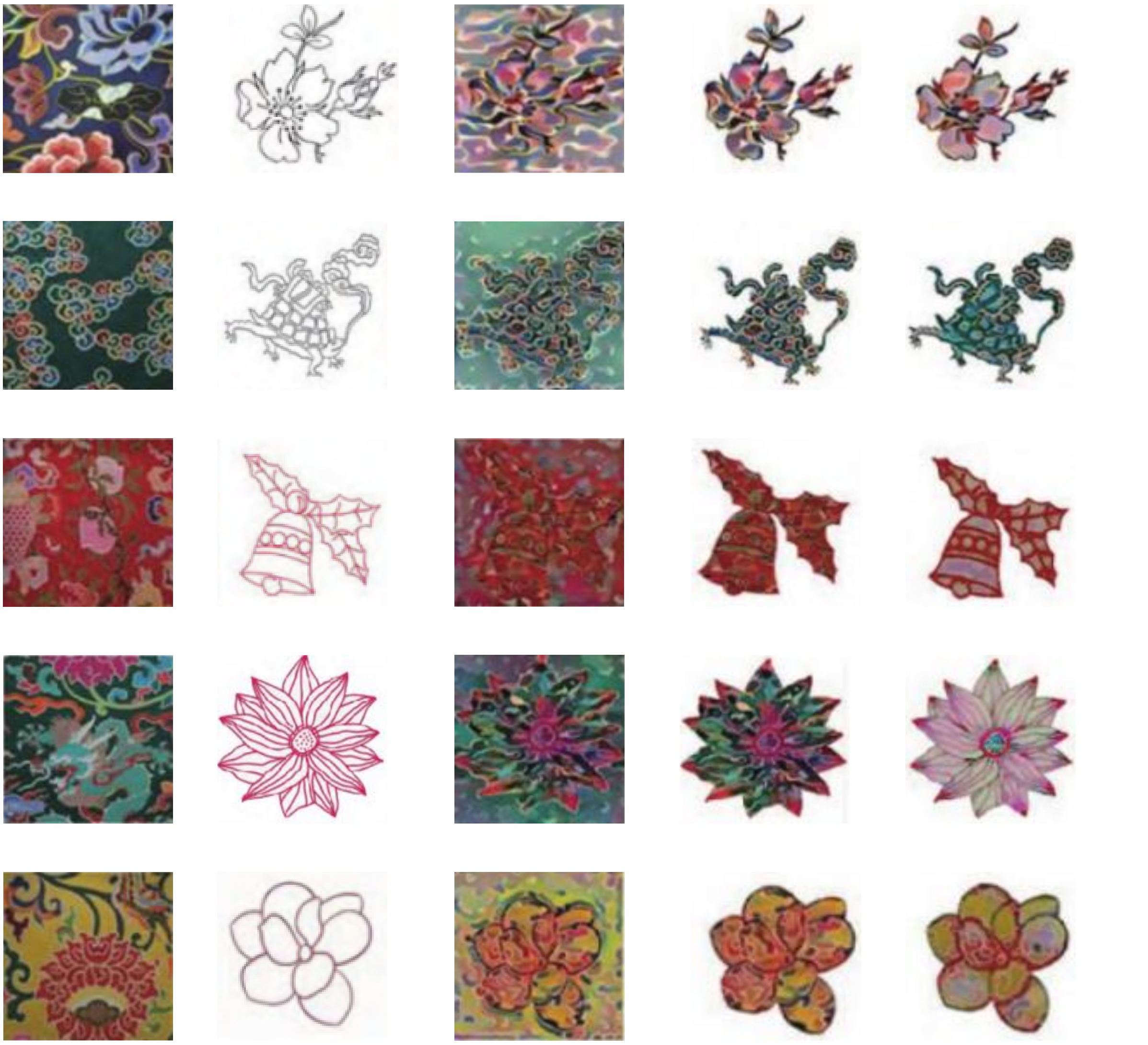

Figure 5. Style migration output diagram

It can be seen that thecolor of the composite image directly generated by the original migration model is mixed, and it is difficult to distinguish the shape and content of the main pattern. This is because the convolutional neural network learns the color features of the image, including the brightness, saturation and distribution of the color, when extracting the features of the style map and the content map, resulting in the corresponding transfer between the color pixels. The content map of line sketch only contains the contour color information, which can not form the corresponding transfer, resulting in the color mixing of the composite effect image and the semantic ambiguity of the target pattern. In the local migration results, the local migration model with mask map can improve the definition of contour by separating the pattern from the background. In the local transfer of color optimization, color loss is added to the optimization model based on the mask diagram. The color of lotus petals is mainly pink, and the color of stamens is mainly green. The outline of the bell is dark red, the blank part is light; The mixed color of the turtle body is reduced, and the main color is green. The optimized model not only improves the definition of the outline, but also reduces the color difference within the pattern and improves the semantic recognition of the pattern.

4.2. Analysis of Experimental Results

For the analysis of the experimental results, there are two stages here: firstly, the experimental results are analyzed from a subjective perspective, using a questionnaire survey method. 20 volunteers are recruited to generate style transfer output maps based on three algorithms: the original transfer algorithm [15], local transfer algorithm [16, 17], and color optimization local transfer algorithm. The clarity of the semantic content of the pattern is evaluated, with a score set at 1-5 points, The easier the pattern content is to recognize, the higher the score. Calculate the mean of the output graphs of the three algorithms for 20 volunteers, and the results are shown in Figure 6.

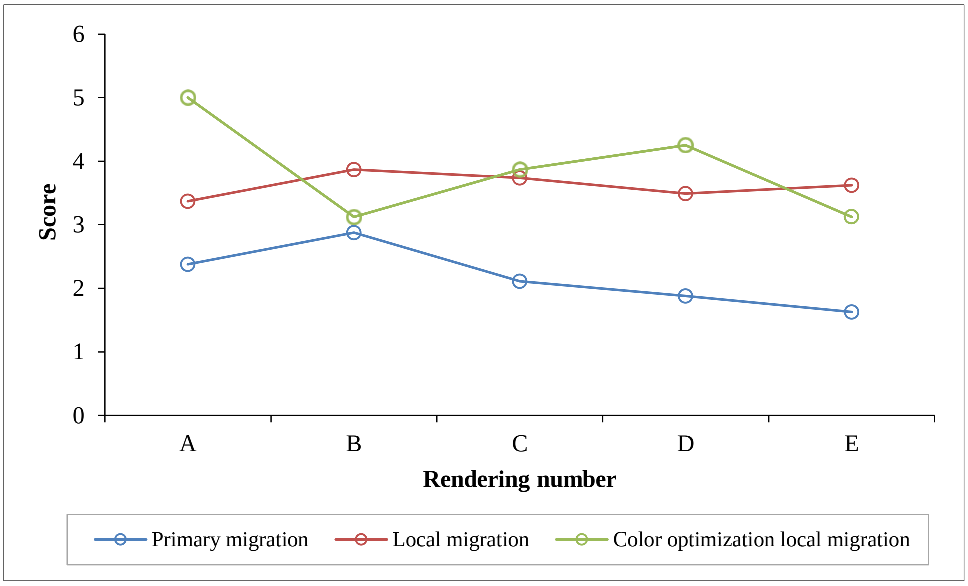

Figure 6. The output graphs of the original migration, local migration and color optimization local migration are used to calculate the survey scores

It can be seen that the mean values of the original migration, local migration and color optimized local migration models are 2.17, 3.61 and 3.87, respectively. Therefore, the color-based local transfer model proposed in this paper improves the semantic content clarity of the main pattern through color optimization on the premise of realizing local style transfer. Second, the experimental results are analyzed on the objective surface, mainly to analyze the time consuming of the algorithm for the quality of the output image of style transfer. The method used here is structural similarity (SSIM), which is defined by pixel image as the combination of three different factors: brightness (l), contrast (c) and structure (s)[18-20]. The mean is used as an estimate of brightness, standard deviation as an estimate of contrast, and covariance as a measure of structural similarity. Each time, the window with D on the picture is calculated, and the average value of all Windows is obtained as the structural similarity of the whole image. The structural similarity value ranges from 0 to 1, and the closer the value is to 1, the higher the similarity between the two images. The calculation formula is shown in Equation 7.

$$\mathrm{SSIM}(a,b)=\frac{(2\mu_a\mu_b+c_1)(2\sigma_{ab}+c_2)}{(\mu_a^2+\mu_b^2+c_1)(\sigma_a^2+\sigma_b^2+c_2)} \tag{7}$$

In the formula, the mean of sample a is represented by μ_a, and the mean of sample b is represented by μ_b; The variance of sample a is represented by σ_a, and the variance of sample b is represented by σ_b; The covariance of a and b is represented by σ_{ab}, and c_1 and c_2 are two constants to avoid division by zero. In order to comprehensively analyze the migration effect, the paper calculates the SSIM value (G_s, G_c) of the output result, style graph and content graph respectively, and takes the mean value of G_s and G_c as the comprehensive similarity index. The size of the composite effect map, style map and content map is set uniformly at 224*224 pixels, and the structural similarity of the migration output map is calculated using SSIM algorithm. The results obtained by local migration algorithm and color optimization local migration algorithm are shown in Table 1.

Table 1. Structural similarity of output graph under local migration algorithm and color optimization local migration algorithm

Picture number	Local migration algorithm			Color optimization local migration algorithm		
	G_s	G_c	$\frac{1}{2}(G_s+G_c)$	G_s	G_c	$\frac{1}{2}(G_s+G_c)$
A	0.05	0.45	0.25	0.06	0.65	0.35
B	0.14	0.71	0.42	0.17	0.71	0.44
C	0.07	0.53	0.30	0.08	0.58	0.33
D	0.08	0.70	0.39	0.07	0.71	0.39
E	0.06	0.71	0.38	0.06	0.70	0.38

It can be seen that there is little difference between the two migration models in terms of style similarity, but in terms of content similarity, the optimization algorithm is generally higher. The average similarity of the local migration algorithm is 0.348, while that of the local migration algorithm based on color optimization is 0.378, which is 8.62% higher than that of the local migration algorithm. In addition, the local migration algorithm and the color optimization local migration algorithm were respectively used on the RTX3080TI to perform 1600 iterations on the experimental images, and the required processing time is shown in Table 2.

Table 2. Running time of the two algorithms after 1600 iterations

Picture coding	Local migration algorithm	Color optimization local migration algorithm
A	13.42	12.31
B	13.56	12.56
C	13.81	12.68
D	13.61	12.45
E	13.83	12.34
Mean value	13.65	12.46

It can be seen that the average running time of the local migration algorithm is 13.65s, and the average time of the local migration algorithm for color optimization is 12.46s when color processing is added under the same configuration. On the surface of the data results, the optimized migration algorithm can quickly obtain a stylized image that is more similar to the structure of the content map, which is conducive to realizing the migration of the Yunjin style of the line manuscript pattern.

5. Conclusion

This study mainly found that the average comprehensive similarity of the local transfer algorithm is 0.348, while the average of the local transfer algorithm based on color optimization is 0.378, which is 8.62% higher than the local transfer algorithm. After 1600 iterations, the average time required for the local migration algorithm to run is 13.65 seconds, while the color optimization local migration algorithm runs in 12.46 seconds. The time difference between the two is 1.19 seconds. Although the time difference is not significant, the color optimization local migration algorithm still has some improvement, which can confirm the feasibility of the Yunjin pattern style migration color optimization algorithm. Compared with other studies, the article uses empirical comparison to test the advantages and disadvantages of color optimization local transfer algorithms, breaking the traditional framework of theoretical analysis. This is relatively avant-garde in promoting the development of cloud brocade patterns, with certain advantages, but also has certain limitations. If the number of iterations is too high, it will inevitably cause some interference to the algorithm operation and require subsequent optimization and adjustment. Overall, this study provides new options for the selection and development of algorithms for transferring the style of Yun brocade patterns, which can further promote the development of Yun brocade patterns. This has a certain role and contribution to the inheritance and preservation of intangible cultural heritage, and it is recommended to apply it in practice in the future. In addition, in the future, algorithms will be continuously optimized to ensure the quality of image migration while reducing runtime.

6. Declarations

6.1. Data Availability Statement

The data presented in this study are available in the article.

6.2. Funding

The author received no financial support for the research, authorship, and/or publication of this article.

6.3. Institutional Review Board Statement

Not applicable.

6.4. Informed Consent Statement

Not applicable.

6.5. Declaration of Competing Interest

The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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