Journal of Fiber Bioengineering and Informatics 16:1 (2023) 75–85

Cite as: J. Zhang et al.
doi:10.3993/jfbim02171

Style Transfer Technology of Batik Pattern Based on Deep Learning*

Jing Zhang, Yan Jiang*

Beijing Institute of Fashion Technology, Chaoyang, Beijing, 100029, China

Abstract

AI painting has recently come into public view, improving the efficiency of users' creations. At present, the research and application of popular products such as characters and landscapes are more, but the research of Miao batik patterns is lacking. Therefore, this paper studies the style transfer of batik patterns from two aspects. First, a local style transfer model of batik patterns with enhanced edges is proposed. The loss function is composed of local content loss, local style loss and Laplacian loss, and the generated images have good performance in detail texture and color space. The other is to use the existing model in the AI painting tool Stable Diffusion for style transfer of batik patterns. It performs well in running time and memory occupation, but the generated image cannot inherit the style and content images well in color and detail.

Keywords: Style Transfer; Edge Enhancement; Mask Diagram; Miao Batik Pattern; Stable Diffusion

1 Introduction

Miao costume patterns are an important carrier of Miao culture. Their patterns are characterized by the interweaving of fantasy and truth, and the combination of abstract and concrete techniques, giving people a free, flexible, and imaginative visual experience [1]. In the past, pattern design was completed by textile computer-aided design software [2, 3]. However, with the development of computer technology, more research has shifted towards applying deep learning to the field of textile and garment [4-6]. Therefore, the style transfer between Miao clothing pattern images and artistic style images can better generate novel artistic patterns and realise innovative designs of patterns. It plays an important role in the inheritance and development of Miao costume culture.

Style transfer technology based on deep learning is a new means of image processing; its main task is to transfer the style of one image to another. At present, there are three main types

*Project supported by the Humanities and Social Sciences of Ministry of Education Planning Fund "Research on Digital Design and Communication of National Fashion Clothing from the Perspective of Cultural Confidence" (22YJAZH037).

*Corresponding author.
Email address: jsjjy@bift.edu.cn (Yan Jiang).

1940–8676 / Copyright © 2023 Textile Bioengineering and Informatics Society
Mar. 2023

of style transfer techniques: Style transfer based on VGG (Visual Geometry Group) [7], image generation based on GAN (Generative Adversarial Network) [8] and image generation based on Diffusion [9]. Style transfer based on the VGG model is proposed by Gatys, which extracts advanced abstract features of images through a pre-trained VGG model to realize distribution matching of feature space as well as constructed Gram matrix as the representation of image style features. By iteratively optimizing the initial white noise image, the differences of content features and style features between the generated image and the input image are minimized, and image style transfer is realized. Subsequently, the style transfer technology based on VGG has received extensive attention and research [10,11]. This kind of algorithm can well represent the style. However, the details and depth information of the content are difficult to retain, and it relies on the feature extraction network with huge parameters. Gan-based image generation was proposed by Goodfellow, which makes the generative network G and the discriminative network D compete with each other. G is committed to generating fake data, and D is committed to identifying fake data. Many researchers have used generative adversarial networks for image style transfer [12,13]. This algorithm can make images' style transfer effect more realistic. However, the stability of the model is not high, prone to mode collapse or low-quality output, and it needs to rely on a large amount of data and carefully adjust the hyperparameters and loss function. Diffusion-based image generation was first proposed by Jascha [14], and the DDPM (Denoising Diffusion Probabilistic Models) model proposed by Jonathan [15] in 2020 has shown excellent results in image generation tasks. Diffusion models receive much attention and have gradually replaced GAN as the mainstream. Its basic principle is to gradually add Gaussian noise, namely labels, to the original image in the forward process to help the neural network learn denoising, to gradually predict the target distribution in the backward process to obtain the denoised image. Diffusion models can also be used for style transfer of images [16,17]. These algorithms can generate high-quality images in a continuous latent space but require a large model capacity.

The research on style transfer technology of traditional clothing patterns has just started in recent years, mainly focusing on the original generation of traditional patterns. For example, Hou applied style transfer technology to generate cross-stitch technology of Miao clothing patterns [18]. Deng proposed an improved neural style transfer algorithm, which realised the transfer of brocade style to any content image [19]. In the innovative generation of traditional patterns, Zeng used two rapid style transfer techniques to transfer traditional Xilankapu patterns and icons to generate patterns with modern pattern semantics and strong traditional Xilankapu geometric style [20]. Wu proposed ClothGAN, which uses generative adversarial networks to generate new clothing styles and then uses style transfer algorithms to obtain Dunhuang style patterns [21]. However, due to traditional patterns' complex structure and variable lines, there is a high demand for details and textures in style transfer. However, current research in the field of innovative generation of traditional patterns mostly focuses on the transfer of different styles, and lacks improvement in the clarity of generated pattern textures.

The current image style transfer algorithm has problems with blurry edge details and uneven color in Miao batik pattern synthesis. Therefore, based on the original transfer model, this paper proposes a local style transfer method of batik pattern based on edge enhancement, which can effectively improve the effect of local pattern transfer and edge detail enhancement. In addition, this paper applies the open source tool Stable Diffusion to carry out the style transfer of Miao batik patterns on the existing model, and compares and analyzes the generation effect, to obtain the appropriate parameter Settings, which provides reference for users of this tool. In short, the generation of innovative patterns through style transfer technology can provide creative

inspiration for professional designers and improve efficiency, but also be applied to clothing textiles through industrial ways such as printing and dyeing, broadening the transmission channels of Miao patterns.

2 Local Style Transfer of Batik Pattern Based on Edge Enhancement

2.1 Methodology

Since Gatys proposed a style transfer model based on convolutional neural network, neural network has been widely used in image feature extraction because of its fast extraction of high-level abstract features and strong semantic representation ability. In this paper, only the pattern itself is transferred in style, and the current image style transfer algorithm has problems such as blurred edge details and uneven colors in the synthesis of Miao batik patterns. Therefore, the mask map of the target area is used as the conditional input to improve the mixing of front and back scenes of the batik pattern transfer effect map. Two processing methods, Laplacian loss and edge information superposition, are also used to solve the problem of unclear edges of the pattern.

The basic steps of the style transfer method of batik pattern based on edge enhancement are as follows [22], and the specific flow chart is shown in Fig. 1.

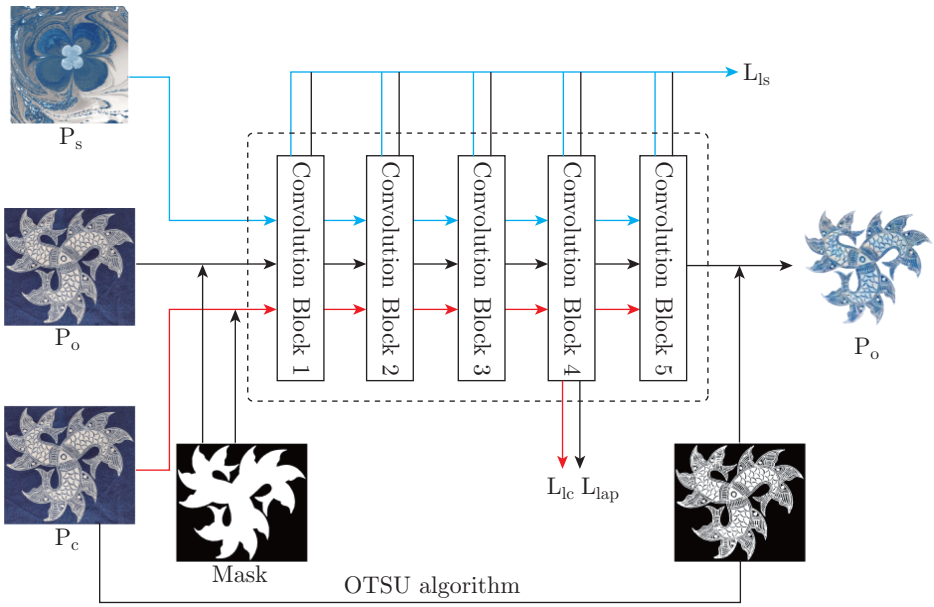


Fig. 1: Flow chart of the local style transfer algorithm of batik pattern based on edge enhancement

(1) Input content image P_c, style image P_s, mask of content image;

(2) Initialize the output image P_o, and generally initialize the output image as a content graph;

(3) Iterative cycle: calculate local content loss $L_{lc} = \frac{1}{2}\sum_{l\in\{l_l\}}(F^l(P_{lc}) - F^l(P_{lo}))^2$, calculate local style loss $L_{ls} = \frac{1}{2}\sum_{l\in\{l_s\}}(G^l(P_s) - G^l(P_{lo}))^2$, calculate Laplacian loss $L_{lap} = \frac{1}{2}\sum_{l\in\{l_c\}}|D(F^l(P_c)) - D(F^l(P_o))|$, calculate total loss $L_{total} = \alpha L_{lc} + \beta L_{ls} + \gamma L_{lap}$, and then update the output image P_o.

(4) Extract the edge information of the content image and overlay it into the output image;

(5) Output the image.

2.2 Experimental Results and Analysis

2.2.1 Experimental Environment

The experiments in this paper were run on a desktop computer with an Inter(R) Core(TM) i7-12700KF 3.60 GHz processor, 32 GB memory, and NVIDIA GeForce RTX 3 090 graphics card. With batik pattern as the content image and modern design image as the style map, the shortest side size of the picture was set as 224 pixels, Adam model optimizer was adopted, the number of iterations is 2 000, the learning rate was set as 3×10^{-3}, the content loss layer was selected as 'conv4-2', and the style loss layer was selected as 'con1-1', 'conv2-1', 'conv3-1', 'conv4-1', 'conv5-1'. The experimental results show that the migration effect is better when the weights of style loss layers are set as 1, 0.8, 0.5, 0.3 and 0.1, and coefficient α, β and γ are set as 1, 1×10^5 and 5×10^3.

2.2.2 Comparative Analysis

To verify the effectiveness and feasibility of the proposed method, the same content and style loss weight of the proposed method, original migration algorithm and local migration algorithm are used to generate migration effect diagrams. The experimental results are shown in Fig. 2. As can be seen from Fig. 2(c), the contour of the composite image generated directly by the original migration model is fuzzy, and the migration of the rear scene restricts the migration of the foreground to a certain extent, resulting in the migration effect cannot be concentrated on the foreground. After adding the mask map to use local loss, the migration effect has been significantly improved, as shown in Fig. 2(d). However, there are still problems, such as unclear

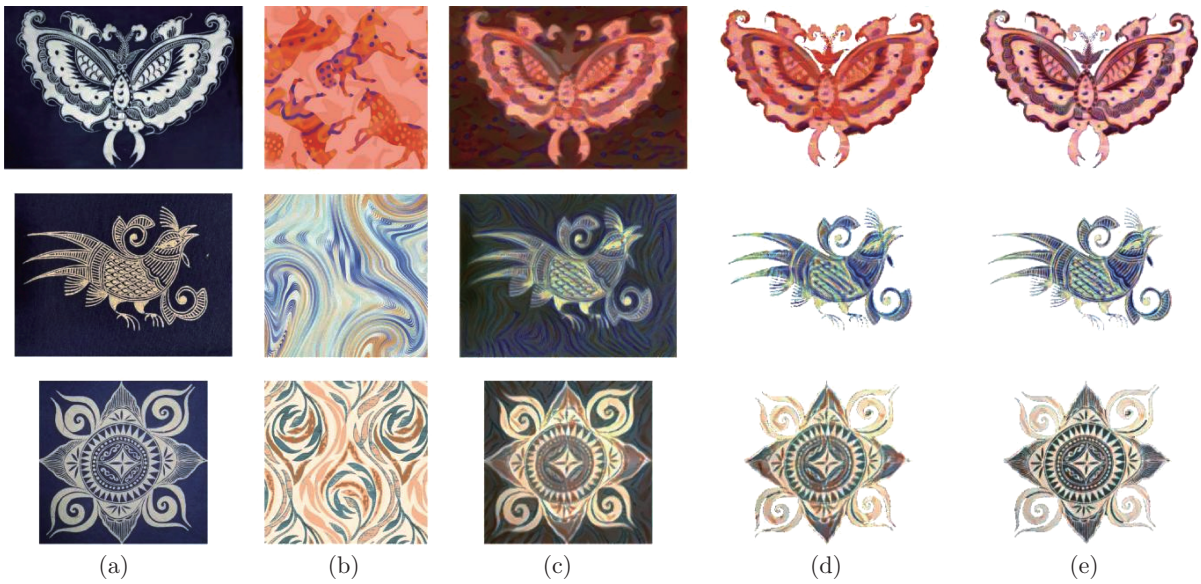


Fig. 2: Comparison of experimental results: (a) Content image; (b) Style image; (c) Original algorithm; (d) Local style transfer algorithm; (e) Algorithm of this paper

detail lines and uneven color distribution. In this paper, based on local losses, Laplacian losses and edge information superposition processing are added to generate the graph, as shown in Fig. 2(e). It can be seen that the overall line details of the butterfly, bird pattern and pomegranate pattern are significantly enhanced, and the color distribution is uniform and clean.

2.2.3 Objective Evaluation

There are several methods to objectively evaluate the effect of image stylized: structure similarity (SSIM), peak signal-to-noise ratio (PSNR) and mean squared error (MSE) [23]. To comprehensively evaluate the migration effect, SSIM, PSNR and MSE values were calculated between the content graph with mask and the generated graph, and the results are shown in Table 1. It can be found that the structural similarity average of the generated graph obtained by the optimization algorithm is 0.887 6, which increases by 18.19%, the peak signal-to-noise ratio is 20.358, which increases by 14.03%, and the mean squared error is 0.018 4, which decreases by 47.83%. The results of this study show that the proposed optimization algorithm can effectively achieve style transfer of batik patterns, improve performance in terms of structural similarity, peak signal-to-noise ratio and mean square error, and improve visual quality.

Table 1: Quantitative statistical results of stylized experiments

	SSIM			PSNR			MSE		
	c	d	e	c	d	e	c	d	e
1	0.704	0.682	0.860	14.580	13.729	18.270	0.035	0.042	0.015
2	0.847	0.834	0.918	19.679	18.502	21.501	0.011	0.014	0.007
3	0.701	0.715	0.862	17.306	17.846	21.510	0.019	0.016	0.007

3 Style Transfer of Batik Pattern Based on Stable Diffusion

Stability AI officially released stable Diffusion in August 2022. Its open source has greatly reduced the threshold for users to create AIGC (AI Generated Content), attracting widespread attention and public use. Stable Diffusion has a strong understanding of generating contemporary art images and is good at depicting the details of images. However, to restore these details, it needs very complex and detailed instructions in image description, which is more suitable for generating complex graphics with more creative details. It may be slightly weak in creating ordinary images. The characteristics of Miao costume patterns are creative, and the specific objects are disassembled to form a new artistic image and aesthetic space, which is rich in imagination and creativity. Therefore, in theory, Stable Diffusion is suitable for style transfer of Miao costume patterns.

3.1 Methodology

The technical basis of Stable Diffusion comes from the Latent Diffusion Model [24]. At the same time, CLIP (Contrastive Language-Image Pretraining) is used as the text encoder to enable the

model to understand the semantic relationship between images and text. There is also the option of using the ControNet neural network model to control the inputs to the model, and influence and correct the results of the stable diffusion model.

In the Stable Diffusion WebUI interface, there are two innovative image generation methods, txt2img and img2img, both of which can accept the input of ControNet model. To implement style migration, ControNet needs to select the Shuffle preprocessor to implement style migration and the Lineart preprocessor to constrain the outline of the image. On this basis, we need to select the existing base model and VAE model and adjust the relevant parameter Settings, including the number of iteration steps, sampling method, redraw size, prompt word lead coefficient, redraw amplitude, etc. Therefore, the control variable method is used to compare and analyze the different parameter Settings in order to find the parameter configuration suitable for the style transfer of batik pattern.

3.2 Experimental Results

Using the same model and parameter Settings, compare txt2img and img2img, and the result is shown in Fig. 3. It can be seen that txt2img results (a) have randomness and uneven color distribution; img2img (a) can perform style transfer by uploading a mask, which can only be done on the pattern part of the image. Therefore, img2img is suitable for the needs of this paper.

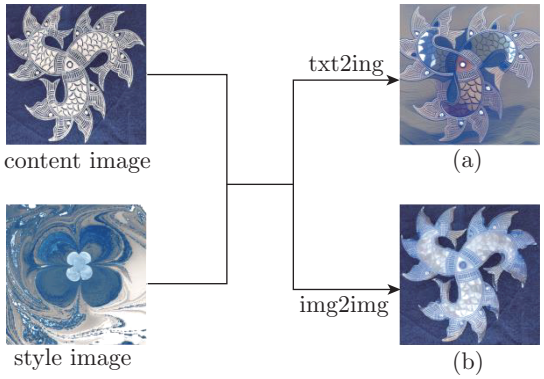


Fig. 3: Style transfer effect comparison: (a) txt2img generated image; (b) img2img generated image

At present, most of the existing basic models are aimed at figures and landscapes, and there is no model aimed at Miao batik patterns. Therefore, this paper compares the commonly used universal large models, including deliberate-v2, stable-diffusion-v1-5, bp_mk3, anything-v5-PrtRE, etc. The commonly used VAE models include None, ClearVAE, and vae-ft-mse-840000-ema-pruned, and the generation effect comparison is shown in Fig. 4. It can be seen that the rose red color which does not exist in the style image appears in the eyes of fish, and the color distribution is uneven. Comprehensive analysis shows that the effect is better when the basic model is stable-diffusion-v1-5 and the VAE model is vae-ft-mse-840000-ema-pruned.

There are more than 20 sampling methods in Stable Diffusion WebUI. Euler a, DPM++ 2M Karras and DPM++ 2M SDE Karras are found to be effective by preliminary comparison. The value of the redraw amplitude is 0-1. After preliminary comparison, it is found that the closer the value is to 1, the closer the image is to the style image, and the closer the value is to 0, the more similar it is to the content image. The preliminary limit value range is 0.4-0.6. The

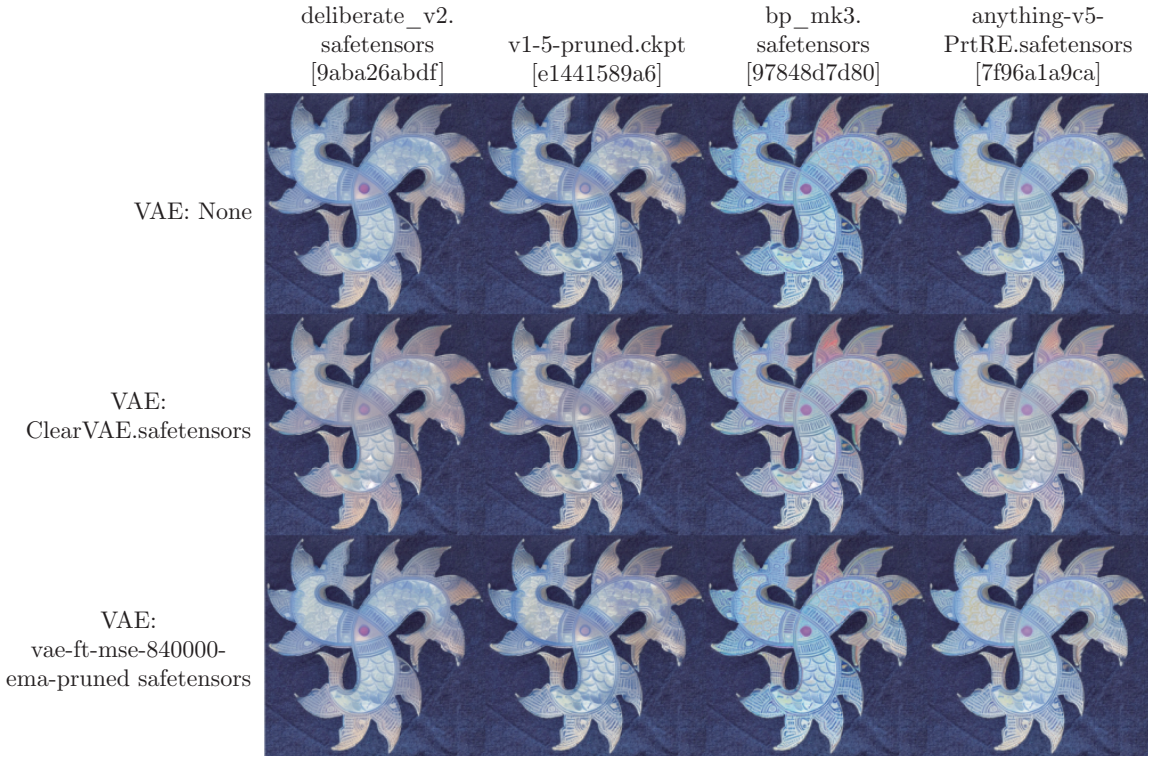


Fig. 4: Comparison of the generation effect of basic model and VAE model

sampling method and redrawing amplitude are further compared, as shown in Fig. 5. It is found that the Euler a sampling method is better than the DPM sampling method, and the best results are obtained when the redraw amplitude is 0.55.

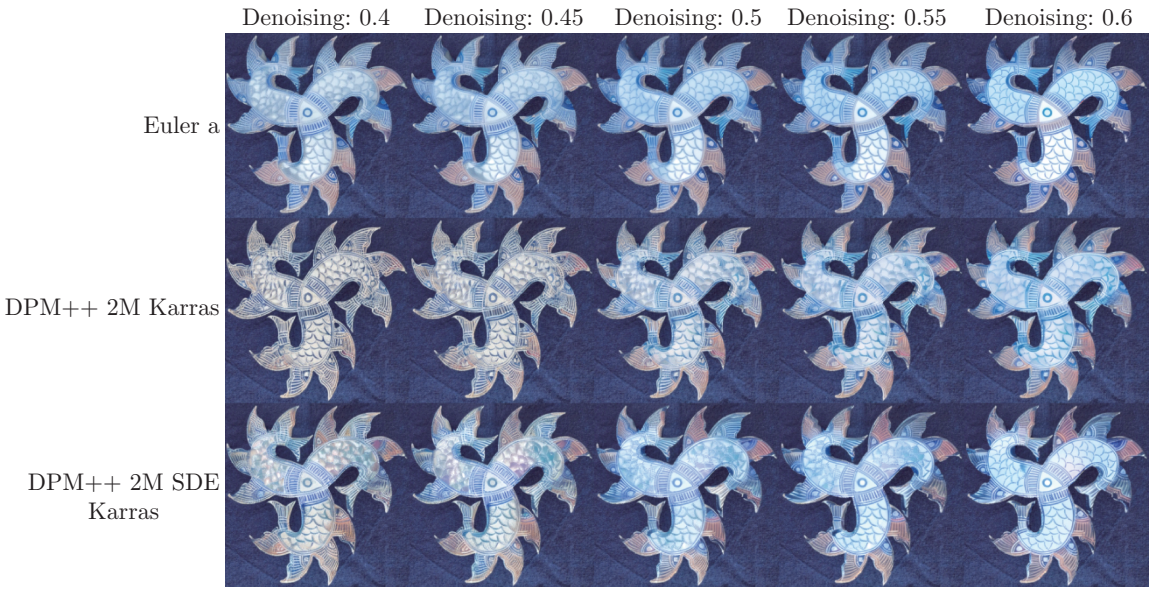


Fig. 5: Sampling method and redraw amplitude comparison

The number of iteration steps is generally 20-50. Under the above parameter configuration, the generation effect is compared when the number of steps is 20, 30, 40, and 50, respectively. It is

found that there is little difference in the effect of graph generation. To save time, the number of iteration steps is 30.

Fig. 6: Multiple generation result

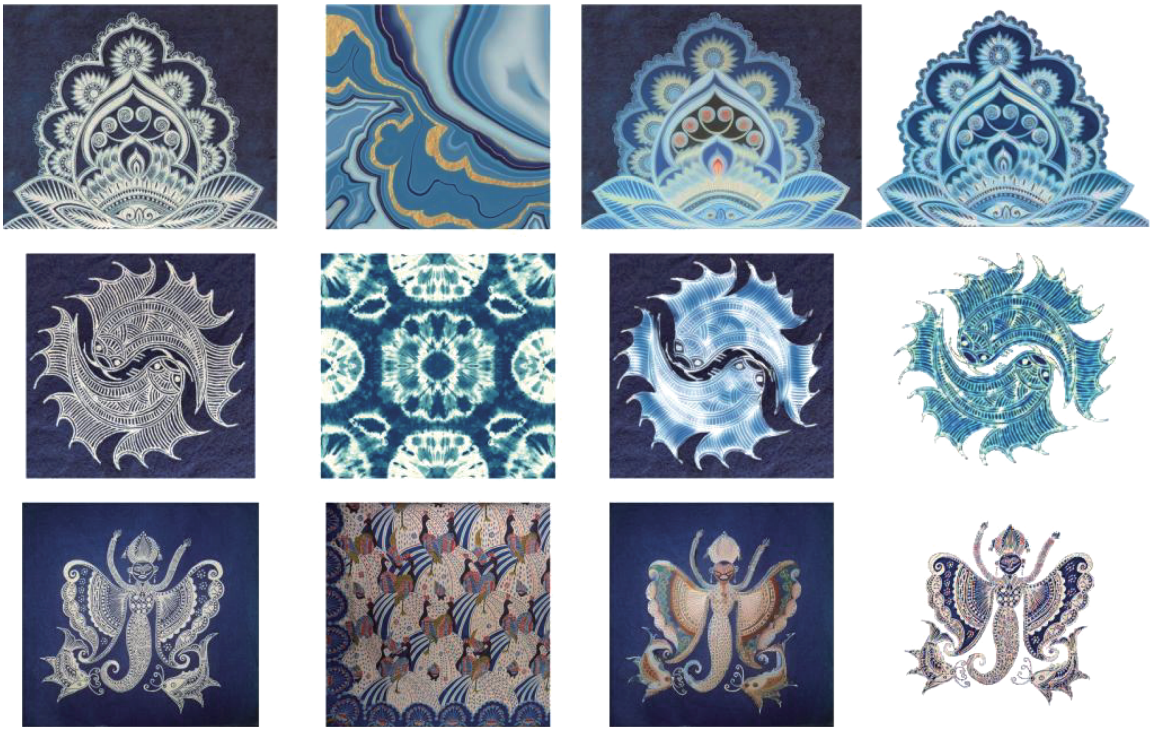
Finally, the minimum values of the height and width of the image were set to 512, the Batch count to 3, and the Batch size to 3, and 9 images were generated to view the generation effect, as shown in Fig. 6. It can be found that only 2 of the 9 pictures have a good effect, there is a problem of uneven color distribution, and it is easy to appear colors that do not exist in the style diagram, and the result of style transfer is not stable.

After the comparison of the above experiments, it can be concluded that when the style transfer of batik pattern is achieved by using Stable Diffusion WebUI, the specific operation method is as follows: upload the content image and corresponding mask in the Inpaint upload interface of img2img. The Shuffle and Lineart preprocessors in ControNet were configured. The basic model was stable-diffusion-v1-5, the VAE model was vae-ft-mse-840000-ema-pruned, the sampling method was Euler a, and the redrawing amplitude was 0.55. The number of iteration steps is 30. After multiple batches of image generation, the desired image can be obtained.

3.3 Comparative Analysis

The effect of Stable Diffusion and the local style transfer method of batik pattern based on edge enhancement are compared and analyzed for multiple groups of images, as shown in Fig. 7. It can be seen that when Stable Diffusion is used for style transfer of swirls, yin-yang fish and butterfly mother patterns. The color of the generated image differs from the style image, and the local details are different, but the overall visual appearance is strong. When using edge-enhanced local style transfer, the generated image can well inherit the color of the style image and preserve the detail structure of the content image. The symmetrical structure of the image can also maintain symmetry in color.

Regarding running time and memory usage, Stable Diffusion shows a strong ability. When processing the image of $512 * 512$ pixels, the memory usage is about 7 G, and the image can be generated for 10 s, while the VGG model needs to consume more computing resources. To



(a) (b) (c) (d)

Fig. 7: Effect comparison: (a) Content map; (b) Style diagram; (c) Style transfer of batik pattern based on Stable Diffusion; (d) Local style transfer of batik pattern based on edge enhancement

process an image of the same size, the memory consumption is about 13 G for 2 000 iterations. It takes about 15 minutes to generate the image.

The comprehensive comparison shows that although the local style transfer of batik pattern based on edge enhancement takes a long time, the quality of the generated image can balance the structure of the content image and the color of the style image, and the generated results are stable. Local style transfer of batik pattern based on Stable Diffusion can quickly generate multiple images, but it needs to adjust more parameters, which is easy to produce colors that do not exist in the style image, and the generated results are not stable enough.

4 Conclusion

In this paper, two deep learning methods are used to transfer the style of batik patterns. The first is to propose a local style transfer algorithm of batik patterns based on edge enhancement, which effectively solves the problems of color mixing, edge line blurring, and uneven color distribution in the front and back scenes in the process of batik pattern style transfer. However, the VGG19 model takes a long time to train and takes up a large memory when dealing with reresolution images. The other is to use the existing model in the open source platform Stable Diffusion for batik pattern style transfer. This method has high efficiency and relatively small memory occupancy, but the quality of the generated image is not high, and it can not be very compatible with the details of the content image and the color of the style image. Therefore, subsequent improvements can be made from two aspects: one is to reduce the training time of VGG19, and the other is to use Stable Diffusion to train models belonging to Miao batik patterns.

Acknowledgement

This paper is sponsored by the Humanities and Social Sciences of Ministry of Education Planning Fund "Research on Digital Design and Communication of National Fashion Clothing from the Perspective of Cultural Confidence" (22YJAZH037).

References

[1] Long J. The evolution of the Miao people's silver ornaments in southeast Guizhou. Art Panorama: 2009; 3: 74-75.

[2] Liu SY, Yuan GX. Application of visual illusion patterns on modern women's knitwear design. Journal of Fiber Bioengineering & Informatics: 2021; 89-100.

[3] KyoungOk K, Takanari K, Yuu T, et al. Effect of fabric pattern and color on impression evaluation of textile images rendered by a textile simulator. Journal of Fiber Bioengineering & Informatics: 2016; 1-18.

[4] Wang SS, Huang DZ, Jia HY, et al. Adjacent local binary patterns based on color space fusion for color image classification. Journal of Fiber Bioengineering & Informatics: 2015; 783-790.

[5] Jing JF, Chen S, Li PF. Automatic defect detection of patterned fabric via combining the optimal gabor filter and golden image subtraction. Journal of Fiber Bioengineering & Informatics: 2015; 229-239.

[6] Masayuki Takatera, KyoungOk Kim. Improvement of Individualized Pattern Making Using Surface Flattening Technique. Journal of Fiber Bioengineering & Informatics: 2013; 467-480.

[7] Gatys LA, Ecker AS, Bethge M. Texture Synthesis Using Convolutional Neural Networks. Advances in Neural Information Processing Systems: 2015; 262-270.

[8] Goodfellow IJ, Pouget-Abadie J, Mirza M, et al. Generative Adversarial Networks. Advance in Neural Information Processing Systems, 2014; 2672-2680.

[9] Sohl-Dickstein J, Weiss E, Maheswaranathan N, et al. Deep unsupervised learning using nonequilibrium thermodynamics. International conference on machine learning. 2015; 2256-2265.

[10] Park DY, Lee KH. Arbitrary style transfer with style-attentional networks. Proceedings of the IEEE/CVF conference on computer vision and pattern recognition: 2019; 5880-5888.

[11] Zhao HH, Rosin PL, Lai YK, et al. Automatic semantic style transfer using deep convolutional neural networks and soft masks. The Visual Computer: 2020; 36: 1307-1324.

[12] Zhu JY, Park T, Isola P. Unpaired image-to-image translation using cycle-consistent adversarial networks. Pro of IEEE International Conference on Computer Vision. 2017; 2223-2232.

[13] Zhao Y, Wu R, Dong H. Unpaired image-to-image translation using adversarial consistency loss. Pro of the 16th European Conference on Computer Vision. 2020; 800-815.

[14] Sohl-Dickstein J, Weiss E, Maheswaranathan N, et al. Deep unsupervised learning using nonequilibrium thermodynamics. International conference on machine learning. 2015; 2256-2265.

[15] Ho J, Jain A, Abbeel P. Denoising diffusion probabilistic models. Advances in neural information processing systems. 2020; 33: 6840-6851.

[16] Choi J, Kim S, Jeong Y, et al. Ilvr: Conditioning method for denoising diffusion probabilistic models. 2021.

[17] Reid M, Hellendoorn V J, Neubig G. Diffuser: Discrete diffusion via edit-based reconstruction. 2022.

[18] Hou KY, Lv J, Liu X, et al. Innovative method of ethnic pattern based on neural style transfer networks. Journal of Graphics: 2020; 4 (41): 606-613.

[19] Deng X, Xu MQ, Wu C, et al. Adaptive style transfer method of brocade crafts based on semantic segmentation. Journal of Beijing University of Posts and Telecommunications: 2021; 1 (44): 117-123.

[20] Zeng Z, Wang J. Research on Innovative Design of Traditional Ethnic Patterns Based on Artificial Intelligence – Taking Xilankapu as an Example. Art Science and Technology: 2021; 16 (34): 25-27.

[21] Wu Q, Zhu B, Yong B, et al. ClothGAN: generation of fashionable Dunhuang clothes using generative adversarial networks. Connection Science: 2021; 33(2): 341-358.

[22] Zhang J, Jiang Y. Local Style Transfer of Batik Pattern Based on Edge Enhancement. Textile Bioengineering and Informatics Society. 2023.

[23] Xydeas CS, Petrovietrovitrovi. A modified valley-emphasis method for automatic thres: 2000; 36 (4): 308-309.

[24] Rombach R, Blattmann A, Lorenz D, et al. High-resolution image synthesis with latent diffusion models. Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2022; 10684-10695.