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Research on Artistic Pattern Generation for Clothing Design Based on Style Transfer

Wenzhe Hu[1,*] *and Yuan Zhang*[1]

[1] Apparel & art design college, Xi'an Polytechnic University, Xi'an, Shannxi, 710048, China

SUMMARY: *To fully integrate key features of the target style in clothing design and effectively control the degree of style transfer, a method for generating artistic patterns for clothing design was designed. Addressing the limited data set of original clothing design patterns, various data augmentation methods, such as translation and scaling, were used to expand the dataset from 2,500 images to 12,500. "Aesthetic fit" and "style identity" were selected as key indicators, and a fourth-order evaluation scale was used to establish a fitness function. An adaptive style transfer model was constructed using the convolutional layers of a ResNet-34 network. Two key loss functions, structural loss and fractal loss, were set, and fractal features of the pattern were extracted using a total loss function. Pattern generation was performed by integrating pattern genes, including abstracting fractal elements from the original clothing pattern, depicting complex structures using an improved fractal function, and outputting the pattern genes as vectors. The application of fractal iteration and fusion techniques in pattern creation was also introduced, providing new insights into the generation of artistic patterns for clothing design. The experiment shows that the fusion rate can effectively regulate the degree of style conversion, and when the fusion is between 40% and 100%, the Baroque style gradually becomes stronger in tie dye patterns. In the design method evaluation, ZR04 and ZR08 are overall excellent, with ZR04 indicator ①, ZR08 indicator ①②, and two indicators ③ all receiving 7 points. The similarity between the generated pattern and the target style color distribution is 0.85, and the similarity between the texture feature vector is 0.82.*

KEYWORDS: *Style transfer; Clothing design; Artistic pattern generation; Detailed texture; Style color distribution*

1 Introduction

Today, the fashion industry is rapidly developing, and consumers' aesthetic preferences for clothing are becoming increasingly diverse and personalized. Clothing design cannot rely solely on traditional styles and fabric innovations. The use of artistic patterns has become key to enhancing uniqueness and artistic value. Style transfer technology is an effective method for incorporating elements of different artistic styles into clothing design, bringing new vitality and creative ideas. By using this technology to transfer classic artistic styles and cultural elements to clothing patterns, we can create visually unique and culturally rich clothing works that meet the market demand for novel and personalized clothing.

Mutia Atika et al. studied pattern generation for three-dimensional cutting inventory problems, focusing on optimizing mathematical models and algorithms to achieve efficient

*hwz1127@126.com
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material utilization and rational pattern arrangement. This approach has significant implications for addressing material waste in production, but it is limited in terms of artistic style integration and creative expression, and does not fully consider the aesthetic value and cultural connotations of the patterns [1]. Kosala Dwidja Purnomo et al. used an iterative function system to generate fractal objects and applied them to lattice decorative design. They were able to create fractal patterns with complex and unique visual effects, bringing new inspiration to decorative design [2]. However, the fractal pattern generation process is relatively fixed, lacking the ability to flexibly transfer and integrate different artistic styles, making it difficult to meet diverse design needs. Liu Suqiong et al. proposed a fast generation method for tie dye patterns based on deep learning and image processing, achieving efficient and automated batch production [3]. However, this method may be overly data-driven, lacking creativity and unique artistic style, and the generated patterns may lack depth and individuality. Omniah Sakr studied the aesthetic value of optical rhythm and its influence on artworks, exploring its importance in artistic creation [4]. However, this research is primarily theoretical, lacking methods and techniques for effectively applying aesthetic elements such as optical rhythm to practical design.

Given the shortcomings in previous research on the integration of artistic styles, creative presentation, aesthetic and cultural considerations, and practical applications, this study explores a fashion design art pattern generation method based on style conversion. This method combines the advantages of deep learning [5] to accurately transfer and integrate multiple artistic styles, taking into account pattern aesthetics, culture, and creative expression. By utilizing advanced algorithm models to optimize the generation process, we aim to improve the quality and diversity of patterns, provide innovative and practical solutions for fashion design, and promote the development and application of this technology in the field of fashion design.

2 Artistic Pattern Generation Design for Apparel Design Based on Style Transfer

2.1 Augmenting Artistic Pattern Data for Apparel Design

The research on clothing design and deep learning art pattern generation requires a large amount of diverse data, but the original art pattern data is limited and difficult to meet the model requirements. Data augmentation technology can address this issue by generating more similar data from a small amount of raw data [6], thereby expanding the training dataset.

There are many common data augmentation methods. Translation transformations can randomly shift an image horizontally or vertically, changing the position of the pattern. Scaling transformations can enlarge or reduce an image by different ratios, allowing the model to encounter pattern features of different sizes. Rotation transformations can also change the orientation of the pattern [7]. For example, for clothing design images containing floral patterns, through translation, scaling, and rotation, the model can learn the characteristics of the flowers at different positions and sizes, as shown in Figure 1.

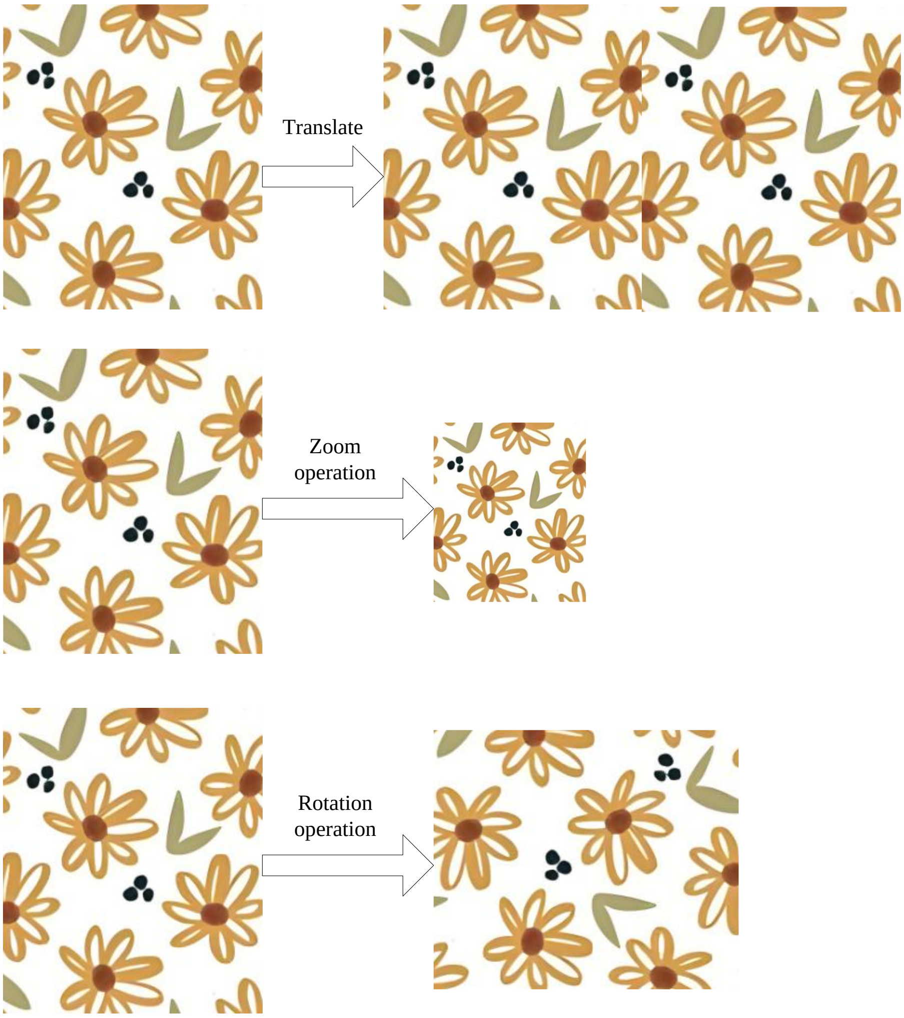

Figure 1: Translation and Scaling of Floral Patterns

This paper uses multiple augmentation methods for clothing design art pattern data. The original dataset contains 2,500 relevant images. The data is augmented by shifting the pattern position, scaling it to adjust its size, and rotating it to change its orientation. The rotation matrix used for rotation is:

$$R(\theta) = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \quad (1)$$

where: θ is the rotation angle.

The contrast is then adjusted using the rotation matrix $R(\theta)$ using the formula:

$$y = \frac{1}{1 + R(\theta) e^{-\alpha(x-0.5)}} \quad (2)$$

Among them, e is the natural logarithm base, x represents the pixel value, and α is the contrast control parameter.

After performing translation, scaling, rotation, and horizontal flipping operations, the dataset is expanded to 12,500 images.

After completing the dataset augmentation, clarifying the dataset type is crucial. Different types of clothing design patterns, such as ethnic and modern minimalist styles [8], have distinct characteristics. Based on the determined dataset type, from among numerous image generation models, we identify those with superior performance in generating clothing design patterns and improve their generation results and quality.

2.2 Establishing a Fitness Function for Clothing Design Patterns

Based on enhanced clothing design pattern data, this paper relies on a well-constructed fitness function to accurately evaluate the quality of individual generated patterns. We select the user's "aesthetic fit" and "style identification" of generated patterns as key metrics for measuring pattern quality.

The fitness function in this paper draws on a comprehensive evaluation model, which uses a four-level evaluation scale to categorize user approval of patterns into four levels: "highly consistent," "basicly consistent," "not very consistent," and "not consistent" [9]. "Highly consistent" corresponds to 4 points, "basicly consistent" to 3 points, "not very consistent" to 2 points, and "not consistent" to 1 point. User ratings are aggregated to generate an aesthetic consistency score. Assume that there are m users participating in the rating, and the aesthetic fit score range is [m, 4m], as shown in Table 1.

Table 1: m Aesthetic Fit Scoring

User Number	Degree of Recognition for the Pattern	Corresponding Score
1	Highly Compatible	4
2	Basically Compatible	3
3	Highly Compatible	4
4	Less Compatible	2
5	Incompatible	1
6	Basically Compatible	3
7	Highly Compatible	4
8	Basically Compatible	3
9	Less Compatible	2
10	Highly Compatible	4

Let the user rating sequence be $[C_i](i=1,2,\cdots,m)$, and let $C_{\max}=[C_{i+m};C_{i+m}\ge C_i]$, $C_{\min}=[C_{i-m};C_{i-m}\le C_i]$, then the C_i value after normalization through [0, 1] is:

$$\overline{C_i}=\frac{C_i-C_{\min}}{C_{\max}-C_{\min}} \tag{3}$$

When the aesthetic fit scores are consistent, the fitness function is determined by calculating the style identification criterion [10]. Let style identity be P, and style identity be calculated using variance:

$$P=\sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(C_i-\overline{C_i}\right)^2} \tag{4}$$

Aesthetic fit $A(C_i)$ is calculated as:

$$A(C_i) = \frac{\sum_{i=1}^{m} C_i}{4m} \times 100\% \quad (5)$$

Assuming that the account for style identity P and aesthetic fit $A(C_i)$ of the fitness are X and Y respectively, $X + Y = 1$, then the fitness function F is:

$$F = X \times \frac{1}{P} + Y \times A(C_i) \quad (6)$$

In conventional algorithms, fitness is determined by a fixed function. However, users' subjective aesthetics vary greatly, and an absolutely objective fitness function does not exist. Therefore, this paper uses user ratings to reflect fitness. By extracting "aesthetic fit" and "style identity" to derive the fitness value, it fully embodies the interactive [11] design concept.

2.3 Extracting Fractal Features from Clothing Design Art Patterns Based on Style Transfer

The principle of extracting fractal features from clothing design art patterns based on style transfer is to construct a style transfer model using the fitness function of clothing design art patterns. This model explores fractal information of clothing patterns [12] and optimizes innovation, making adaptive style conversion more flexible. Figure 2 shows its architecture.

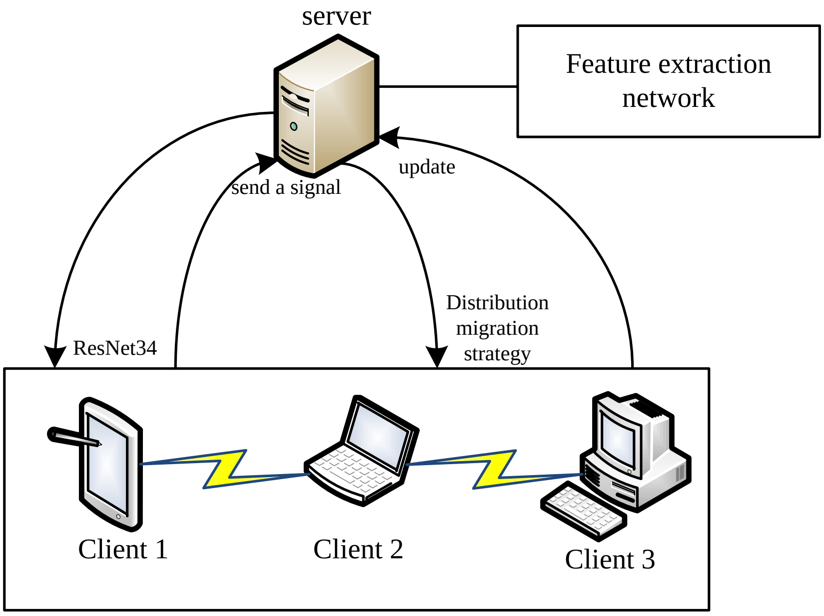

Figure 2: General Architecture of the Adaptive Style Transfer Model

In the adaptive style transfer model of this article, the feature extraction network on the right side adopts the common ResNet series, and ResNet34 is selected as the project. The complete version is not used, but the fully connected layer is deleted and only the convolutional layer is retained [13, 14]. This reduces parameters and avoids wasting computational resources.

This paper uses a plane figure as an example. Starting with an initial square pattern, it is first divided into four smaller squares. The center of each small square is removed to create a hollowed-out effect. This process is then repeated for the remaining eight smaller squares. Through continuous iteration, a complex fractal pattern with self-similar characteristics is ultimately obtained.

To better extract fractal features from clothing design art patterns, two key loss functions are established: structural loss and fractal loss. The structural loss is used to measure the overall structural difference between the generated pattern and the original pattern. It is calculated using cosine similarity and is formulated as follows:

$$S_l = \frac{\sum_{j=1}^{n} U_j E_j}{\sqrt{\sum_{j=1}^{n} U_j^2}\sqrt{\sum_{j=1}^{n} E_j^2}} \tag{7}$$

where: n is the dimension of the vector, U_j is the j th component of the first vector, E_j is the j th component of the second vector.

The fractal loss focuses on the fractal characteristics of the pattern and is determined by calculating the difference in self-similarity at different scales. The formula is as follows:

$$L_l = \sum_{s=1}^{S} \left\| F_s\left(I_g\right) - F_s\left(I_o\right) \right\|^2 \tag{8}$$

Among them, S is the scale number, F_s is the scale s feature extraction operation, I_g is the transformed pattern, and I_o is the original image. Models β and χ have control structures and fractal feature loss weights, with a total loss of two losses multiplied by weights:

$$L_t = \beta \cdot S_l + \chi \cdot L_l \tag{9}$$

Thus, through the total loss function, fractal feature extraction of clothing design patterns based on style transfer is achieved.

2.4 Integrating Pattern Genes to Generate Clothing Design Patterns

This paper argues that clothing design patterns are like unique genetic codes. Their creation involves constructing a framework and filling it with distinctive elements. Key nodes of the framework can be embedded with pattern genes. The areas connected by lines in the figure are the spaces where genes function and exert their effects. To generate clothing design pattern genes with fractal characteristics, the following steps must be followed:

1) Abstract and extract fractal elements from the original clothing pattern. Using professional design analysis tools, we analyze the fractal elements inherent in the pattern, such as self-similar structures and iteratively generated details. Through interactive design software, we precisely determine element types, select key fractal nodes [15-17], and calculate corresponding fractal parameters, such as fractal dimension and number of

iterations.

2) An improved fractal function expression is used to depict the complex structure of the pattern. For self-similar curves, an improved IFS (Iterated Function System) function is used. The general expression of the IFS function is:

$$\begin{cases} x_{d+1} = a_1 x_d + b_1 y_d + c_1 \\ y_{d+1} = a_2 x_d + b_2 y_d + c_2 \end{cases} \tag{10}$$

where: (x_d, y_d) represents the coordinate point after the d iteration, a_1, b_1, c_1, a_2, b_2, c_2 represent the parameter controlling the fractal morphology. By continuously iterating this function, we obtain the coordinate points of a curve with self-similar characteristics, which can then be connected to form a curve.

For fractal patterns with rotational symmetry, we use a rotation fractal function in polar coordinates. Let the polar coordinates be (r, θ), and the rotation fractal function expression be:

$$r_{d+1} = f(r_d) \times \theta_{d+1} = \theta_d + k\frac{2\pi}{h} \tag{11}$$

where: $f(r_d)$ represents the iterative function with respect to radius r, θ_d represents the rotation angle after the d th iteration, k represents the rotation multiple, h represents the symmetry order. This function can be used to generate fractal patterns with rotational symmetry.

3) Output the generated pattern gene in vector form, that is, use the above formula (11) and a small number of key parameter variables to accurately describe the edge contour of the pattern gene [18-20]. The pattern gene represented by the vector has the advantages of small data storage, infinite scalability and no distortion.

Fractal iteration and fusion technology are often used to integrate pattern genes in the creation of clothing design art patterns [21]. Fractal iteration allows a single pattern gene to repeat according to specific fractal rules to form a complex and orderly structure; pattern fusion combines multiple different pattern genes through fractal transformation to create a new and creative pattern.

3 Experiments

3.1 Experimental Development Environment

This paper studies the generation of artistic patterns for clothing design based on style transfer. The development environment is Windows, written in Python, and integrated with the PyTorch framework for its dynamic computational graphs and rich pre-trained models. During the experiment, PyTorch's automatic differentiation and GPU acceleration are used to make the training and inference of the style transfer algorithm more efficient. Libraries such as OpenCV and Pillow are also used to pre- and post-process the input images to preserve the original clothing contour structure. Before the experiment, training parameters were set; see Table 2 for details.

Table 2: Experimental Training Parameter Settings

Serial number	Parameter Name	Parameter Details
1	Initial Total Training Epochs	300
2	Batch Size	32
3	Initial Learning Rate	0.0001
4	Learning Rate Adjustment Strategy	Cosine annealing strategy, reduce the learning rate to 90% of the current value every 50 iterations
5	Optimizer	Adam optimizer
6	Optimization Objective	Minimize the sum of style loss and content loss
7	Loss Trend	When the number of training epochs exceeds 250, style loss and content loss tend to stabilize

For different style transfer tasks, three sub-models are constructed and the corresponding network parameters are set:

(1) StyleGAN: The initial learning rate of the generator/discriminator is 0.0002, with 1500 rounds of training, 64 batches, and 256×256 images.

(2) Neural Style Transfer: The learning rate is 0.00015, the total number of training rounds is 800, the batch size is 16, and the generated images maintain the original clothing size.

(3) FastPhotoStyle: The learning rate is 0.0001, the total number of training rounds is 2000, the batch size is 8, and the generated image size is 512×512 to achieve high-resolution artistic pattern generation.

3.2 Experimental Data

This article focuses on the generation of artistic patterns in fashion design based on style transformation, with a particular emphasis on the color matching, pattern structure, and elements of clothing for children (6-12 years old) and teenagers (13-18 years old). Data comes from widely collected and customized images on the Internet. Three common bottoms, namely dress, skirt and wide leg pants, are selected for research. See Figure 3 for an example.

Figure 3: Examples of Common Bottoms

In terms of color, six colors were selected, encompassing both vibrant warm tones and calming cool tones: orange, purple, green, cyan, brown, and silver. These colors are widely used in fashion and each has its own unique characteristics.

This paper collects image data using a combination of web crawlers and field photography. Web crawlers search for relevant color and clothing style keywords, obtaining images from search engines like Google and e-commerce platforms. These images capture clothing in various scenes, angles, and wearing conditions. Field photography was conducted in selected clothing stores and shopping malls, capturing photos of the actual items. After collection, images were carefully screened to eliminate irrelevant and flawed images to ensure dataset quality. The resulting sample set includes six colors and three common clothing styles, including dresses, with 300 images for each color and style, for a total of 5,400 images.

Initial data collection consists of two parts: a target pattern dataset and a style inspiration dataset. Given the scarcity of open-source tie-dye pattern datasets, we collected 500 tie-dye images through visiting art studios, photographing art exhibitions, and scanning relevant art books to construct the target pattern dataset, and 500 images of different regional cultural styles to construct the style inspiration dataset. The images were normalized and data augmentation techniques were used to expand the dataset, ultimately resulting in 1,200 tie-dye sample images, which were uniformly resolved and named and stored. Some tie-dye sample images are shown in Figure 4.

ZR01 ZR02

ZR03 ZR04

Figure 4: Some Tie-dye Sample Images

After three rounds of feature fusion and optimization, the style transfer algorithm achieves stable output, thereby obtaining key parameters for the generative network. The experiment aims to use tie-dye style patterns as a content baseline and diverse artistic styles such as Bohemian and Baroque as style references. Through model training, the unique characteristics of the selected style patterns are presented, achieving style transfer.

3.3 Experimental Results Analysis

To test the effect of the style conversion based clothing design pattern generation method on tie dye style conversion, taking Baroque style as an example, tie dye style image ZR04 (Figure 4) was used as the content image and Baroque style image as the style image to verify the results of transforming Baroque style into tie dye patterns with different fusion ratios. When the number of training rounds is fixed, the fusion rate parameters are set to 40%, 70%, and 100%, and the conversion results are shown in Figure 5.

The fusion ratio parameter is 40% | The fusion ratio parameter is 70% | The fusion ratio parameter is 100%

Figure 5: Generated Effects after Style Transfer

Figure 5 shows that different fusion ratios produce different generated pattern styles. At a 40% fusion ratio, the pattern retains more of the original tie-dye characteristics, with fewer Baroque elements and limited line complexity and ornateness. Raising it to 70% enhances the Baroque influence, resulting in richer pattern details, more curled and decorative lines, and a more ornate visual effect while still retaining the charm of tie-dye. At 100%, the Baroque style dominates, with fewer traces of tie-dye, and the pattern exhibits typical Baroque complexity and luxury, with dense and refined lines. This shows that adjusting the fusion ratio can effectively control the degree of style transfer, providing flexible creative space for the fusion of tie-dye and Baroque styles.

Score 10 selected clothing art patterns based on three key indicators: ① Whether there is a target style color match and texture; ② Whether to preserve the original clothing style, silhouette, and structural features; ③ Whether the pattern details are fine, whether there are deformations or defects. Using a 7-point scale, 1 indicates complete non-compliance, 7 indicates complete compliance, and the higher the score, the stronger the compliance. Statistically analyze the scoring results and calculate the indicator scores for each mode group, as shown in Table 3.

Table 3: Scoring Results for Clothing Art Patterns

Pattern Code	Score for Indicator①	Score for Indicator②	Score for Indicator③
ZR01	5	6	4
ZR02	6	5	5
ZR03	4	7	6
ZR04	7	4	7
ZR05	5	5	6
ZR06	6	6	5
ZR07	4	4	4
ZR08	7	7	7
ZR09	5	6	5
ZR10	6	5	6

As shown in Table 3, in terms of metric ①, ZR04 and ZR08 scored the highest, both with a score of 7, demonstrating excellent fit with the target style. ZR03 and ZR07 scored lower, indicating a lack of style representation. In terms of metric ②, ZR03 and ZR08 scored 7, effectively preserving the outline and structure of the original clothing style. ZR04, with a score of only 4, was slightly weaker in this regard. In metric ③, ZR04 and ZR08 again lead with scores of 7, demonstrating fine, flawless pattern detail. ZR01, with a score of 4, needs improvement in detail processing. Overall, ZR04 and ZR08 perform exceptionally well, excelling in style presentation, preservation of original features, and detail processing. The differences between different patterns across these metrics indicate that there is room for improvement in style transfer technology for pattern generation in apparel design, providing a clear path for future improvements.

Next, calculate the similarity between the generated image and the target pattern in terms of color and texture. The closer it is, the more complete the fusion will be, and the more prominent the target style features will be. The similarity results between the generated pattern generated by our method and the target style pattern are shown in Figure 6.

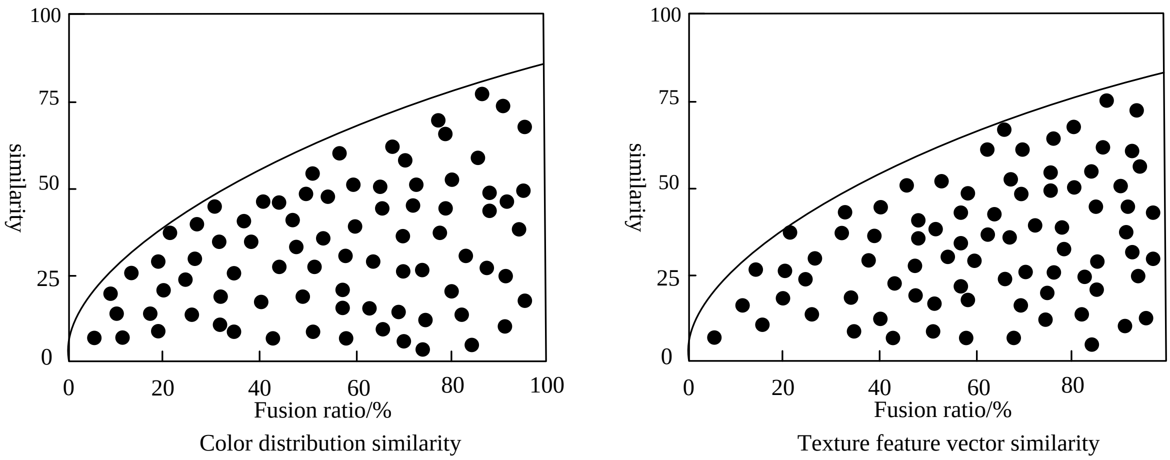

Figure 6: Similarity results between the generated pattern generated by our method and the target style pattern

As shown in Figure 6, the color distribution similarity reaches 0.85, indicating that the generated pattern is highly similar to the target style pattern in terms of color selection, matching, and distribution ratio, replicating its key color characteristics and imparting a consistent visual atmosphere. The texture feature vector similarity is 0.82, indicating that the generated pattern's texture details, such as direction and density, are highly consistent with the target style pattern, effectively presenting a unique texture. Overall, the color distribution and texture feature vector similarities are both close to 1, fully demonstrating that the clothing design art patterns generated by this method fully integrate the target style, accurately reflect key features, and achieve the desired style transfer effect.

4 Conclusion

This article studies the generation of fashion design art patterns based on style conversion, and obtains valuable results, proving that this technology provides an innovative and efficient method for pattern generation. By properly selecting algorithm parameters, it can accurately integrate the characteristics of different style patterns, achieve innovative expression, and meet diverse design needs. The research found that the choice of style image plays a decisive role in the generation effect. Style images with distinct features and strong expressiveness are easier to transfer and produce unique visual effects. The complexity of the content image affects the difficulty and effectiveness of transfer, with simple and clear images better able to carry the style characteristics. The appropriate loss function combination is key to ensuring transfer quality, preserving content structure and incorporating style elements. This research enriches the theoretical system of clothing design pattern generation and provides practical methods and tools. In the future, better algorithms can be explored, combined with artificial intelligence, to achieve automation and personalized generation of clothing design, promote intelligent innovation in the industry, and bring more attractive clothing to consumers.

About the Author

Wenzhe Hu, Female, Han nationality, born on November 27, 1977 in Qingyang, Gansu Province, Master of artistic design, Lecturer. Graduated from the Xi'an Polytechnic University in 2005.Worked in Xi'an Polytechnic University.Her research concentration include fashion design, apparel pattern design and apparel culture, E-mail: hwz1127@126.com, 20050505@xpu.edu.cn.

Yuan Zhang,,Female, Han nationality, born on November 11, 1973 in Xi'an, Shannxi Province, Master of artistic design, Professor. Graduated from the Xi'an Polytechnic University in 2005.Worked in Xi'an Polytechnic University. Her research concentration include performance art, fashion design and image art design, E-mail: 1506750220@qq.com, 19940713@xpu.edu.cn.

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