Research on the Innovation and Design Practice of Traditional Batik Based on StyleGAN-Generated Patterns and Eye Movement Signal Optimization

Yanfei Liu[1], Zixing Li[2]
[1]School for Creative Studies, Yiwu Industrial and Commercial College, Yiwu 322000, Zhejiang, China
[2]Department of Apparel Engineering, Hebei Vocational University of Technology and Engineering, Xingtai 054000, Hebei, China
Corresponding author: Yanfei Liu (e-mail: 15906798205@163.com)

ABSTRACT To address the cultural value and design requirements of batik patterns, this article first generates novel patterns incorporating traditional elements such as peonies and phoenixes based on the StyleGAN neural network. Subsequently, eye movement experiments are conducted to screen visually attractive pattern features and evaluate users' attention distribution toward generated pattern structures. Finally, designers further refine the selected patterns to make them suitable for modern textile design, fabric decoration, and the surface appearance design of functional wearable products. To verify the feasibility of combining the new patterns with contemporary fabrics and engineering-oriented application carriers, design practices are carried out. In particular, the study considers the potential use of patterned textile surfaces in smart fabrics, wearable electromagnetic devices, and antenna-integrated textile products, where visual acceptability and functional integration need to be jointly considered. According to survey results, these designs meet the aesthetic expectations of the audience and show good application potential in textile design, fabric decoration, and the appearance optimization of functional textile products related to wearable electromagnetic applications.

INDEX TERMS batik pattern, stylegan, eye tracking, textile design, wearable electromagnetic devices

I. INTRODUCTION

According to the definition of the Convention for the Protection of Intangible Cultural Heritage issued by UNESCO, traditional handicrafts are considered an integral part of intangible cultural heritage, with ethnic weaving and manual textile dyeing techniques serving as vital manifestations of this cultural continuity. These ancient fabric-making skills represent the historical intersection of community identity and the material evolution of the global textile industry [1]. Batik is a very ancient dyeing technique used by ethnic minorities in China. The anti-dyeing function of wax is utilized in this technique. Firstly, a copper wax knife is dipped in wax solution to draw patterns on the cloth, and then placed in a dyeing vat with dye for immersion dyeing. Finally, after boiling and dewaxing, the patterns are presented. Chinese batik has a very long history, and its rudiments appeared as early as ancient times. At that time, people had already widely used natural dyeing products such as indigo dye and beeswax to make their clothing. In the Tang Dynasty, batik handicrafts were once at their peak. The prosperity of batik culture can be seen in the Tang Dynasty batik artworks collected in the Zhengcang Academy in Japan and the character clothing in the paintings of Tang Dynasty painter Zhang Xuan [2]. Batik art is still popular among the She ethnic group in Fujian, Zhejiang, Jiangxi and other regions of China. The batik process produced by the She ethnic group is excellent, mostly featuring distorted animal and plant patterns, with a full and unique composition. Due to its unique charm and exquisite craftsmanship, it is widely used in She ethnic headscarves, aprons, clothes, skirts, sleeves, and daily necessities, becoming an indispensable art in the lives of She women. It records important life rituals such as religious beliefs, totem worship, folk activities, production and life, marriage, birth, and funeral of She people. The batik pattern reflects the historical changes and social development of the She ethnic group for thousands of years. And this traditional handicraft technique has made the meaning of batik ancient and profound, and after a long history of development, it has formed a unique national artistic style.

In recent years, with the rapid development of digital technology, the protection and inheritance of intangible cultural heritage has gradually shown digital characteristics. In the context of digital survival, protecting and inheriting intangible cultural heritage is not only about repackaging it, but more importantly, inheriting and promoting it culturally. Modern elements have been infused into cultural products and design projects related to intangible cultural heritage by advanced digital technology, rendering them more appealing to the aesthetic tastes of young people [3]. This technology based on neural networks and deep learning algorithms is gradually changing the traditional design patterns and can generate large-scale traditional patterns. Building upon this, the artistic features of traditional batik are investigated in the study by applying generative artificial intelligence to develop novel patterns optimized for modern textile printing and fabric textures, fostering the innovation and diversification of the garment design sector. These AI-generated motifs are engineered to align with both automated weaving constraints and contemporary aesthetic demands, ensuring a seamless transition from digital concept to physical textile production.

II. RELATED RESEARCH

A. SUSTAINABLE DEVELOPMENT OF TRADITIONAL PATTERNS BASED ON DIGITAL TECHNOLOGY

With the rapid development of digital technology in recent years, the sustainable development of pattern and image art in traditional craftsmanship has been promoted, attracting many researchers to devote themselves to the digital protection and inheritance of traditional craftsmanship. This is mainly reflected in several levels. Firstly, a digital resource library for graphic patterns has been constructed. For example, Jack Ma and Zhang Lei [4] utilized the advantages of digital technology to establish digital resources for batik techniques. Zhang Li [5] established a digital pattern resource library for Miao batik. The disadvantage is that if patterns are selected for design based on the digital resource library of these patterns, the selection and evaluation of designers will be subjective. Based on human eye movement information, such as line of sight trajectory or pupil response, the subjectivity problem of designers extracting pattern features can be solved. Secondly, the extraction of traditional pattern features based on the Eye tracking system has attracted active attention from researchers. The Eye tracking system can speculate on the cognitive processing of patterns in the human brain, which can solve the subjectivity problem of pattern element extraction. Hu Shan et al. [6] used eye movement experiments to extract traditional pattern features, taking the Chu lacquer phoenix pattern as an example. By analyzing the sample regions that the subjects focused on, they provided reference for innovative design of traditional patterns. Li et al. [7] revealed the visual pattern of subjects observing traditional handicraft patterns based on the Eye tracking system. Zhang Ning et al. [8] used eye tracking technology to quantify people's intuitive understanding of the characteristics of embroidery culture. By combining eye movement data and subjective evaluation, design elements of the culture were extracted from embroidery, and the feasibility of this design method was verified through design cases. Liu et al. [9] generated visual hotspot maps by using the Eye tracking system to explore people's visual focus patterns on the cultural heritage of the historical center of Chabrag. Doga Gulhan et al. [10] employed a mobile eye tracker to compare the gaze data of visitors towards physical or virtual artworks, as a measure of aesthetic experience differences between virtual and physical environments. In summary, the design and evaluation method of eye movement experiments has good objectivity and operability [11], and has achieved some effective results. Once again, some scholars have conducted simulation studies on batik patterns, such as Yu Yangtao et al. [12], who studied Yunnan batik paintings and simulated the generation and dyeing of ice patterns on fabrics. However, the disadvantage is the limited diversity of generated texture morphology due to the difficulty in obtaining batik patterns. Some scholars have conducted research on the generation of traditional patterns based on Generative Adversarial Networks (GANs). GANs are one of the deep neural networks, which can generate rich and novel patterns. For example, Wu and Zhang [13] used GAN for pattern generation of ancient oil paper umbrellas. Cui Yin et al. [14] took porcelain decorative patterns as an example to construct an intelligent auxiliary design system for porcelain decorative patterns based on adversarial network technology (GAN), reducing the threshold for public participation in traditional handicraft design. These studies have high reference value for AI empowering the generation of traditional patterns.

B. TECHNOLOGY AND APPLICATION OF GENERATIVE ADVERSARIAL NETWORKS

GAN was proposed by Goodfellow et al. in 2014. GAN can learn the data distribution of existing images and generate similar images. It consists of two parts, namely a generator and a discriminator. The generator is used to generate images, while the discriminator is employed to determine the authenticity of the generated images. When the discriminator is unable to distinguish the authenticity of the generated image, training can be stopped. The original GAN network has some problems during the training process, such as the loss function's inability to effectively guide the training process, and the phenomenon of pattern collapse. If the discriminator has strong discriminative ability, the generator may encounter the problem of gradient vanishing, making it difficult for the loss function of the generator to decrease, and the quality of the generated image cannot be guaranteed. Arjovsky et al. [15] proposed WGAN, which introduces Wasserstein distance as the optimization objective. Since Wasserstein distance has strong smoothness, this replacement can fundamentally improve the gradient vanishing problem in GAN networks. In addition, if the discriminative ability of the original GAN discriminator is weak, the discriminator cannot effectively distinguish between the generated image and the real image, and the feedback information it provides cannot correctly guide the generator to update parameters, which will lead to a decrease in the authenticity of the generated image. In response to this issue, Mirza [16] proposed CGAN (Conditional Generative Adversarial Network). Compared with the original GAN, the most notable feature of CGAN is the integration of attribute information y into the generator and discriminator. Attribute information y can represent any label information, such as gender or facial expressions like crying and laughing. The discriminator not only needs to distinguish the authenticity of the generated image, but also has to determine whether the generated image meets the attribute information y. The generated image needs to be both realistic and meet the conditional attributes in order to pass the discriminator. CGAN transforms unsupervised learning into supervised learning, allowing the generator to generate the images we need. SAGAN (Self-Attention Generative Adversarial Networks) [17] was proposed by Zhang et al. to generate more stable and high-quality images during the training process by introducing self-attention. From the perspective of visual effects in generating images, SAGAN's breakthrough is also very significant.

C. LITERATURE SUMMARY

GAN networks can learn the data features of existing images and simulate the generation of new images. Although the original GAN has many drawbacks, the ability of GANs to generate images has continuously improved with the growing number of GAN-derived networks. For example, DCGAN (Deep Convolutional Generative Adversarial Networks) can generate brand new images with significant diversity [18,19]. Although a few researchers have effectively explored the feasibility of using DCGAN in the inheritance and innovation of intangible cultural heritage, some scholars have found that DCGAN generates low resolution product images [20]. Especially for weaving patterns, the shortcomings of DCGAN are more obvious. For example, some scholars have intelligently generated new willow weaving patterns based on DCGAN, and research results show that DCGAN can only learn and make fuzzy weaving patterns. Therefore, the images generated by DCGAN cannot present the specific details of the woven pattern. Although these blurry patterns provide designers with further creative space and imagination, there are significant issues of randomness and subjectivity in the designer's creations. In this article, taking the batik patterns of the She ethnic group in China as the research object, the advantages of the StyleGAN model are summarized. Existing literature in the field of cultural and creative design suggests that GAN generated design drawings can assist designers in their creative design work. However, after GAN generated design drawings, if designers are directly asked to select the generated patterns for creative design work, it will not be objective enough because the selection of patterns generated by GAN by designers has strong subjectivity. The difference in understanding between designers and consumers will lead to a certain degree of disparity in aesthetic preferences of cultural and creative design works. In order to make up for this research deficiency, in this study, the StyleGAN model was first used for pattern generation and design, ultimately forming a pattern resource library. Then, eye tracking technology was utilized for pattern preference experiments. Finally, the designer took these consumer preferred patterns as a source of inspiration for creative design work.

III. PATTERN GENERATION EXPERIMENT BASED ON STYLEGAN

She ethnic batik has high aesthetic value and cultural research value. The phoenix pattern composed of phoenix and peony is a traditional pattern of the She ethnic group. Phoenix and peony patterns, also known as "phoenix rejoicing among peonies patterns" or "peonies attracting phoenix patterns", are considered symbols of love and happiness between couples in the She ethnic group [21]. In this study, traditional phoenix and peony patterns were collected and studied, and based on this, new graphic styles were generated using the StyleGAN network before making batik. The research steps were divided into the following three stages: in the first stage, phoenix and peony images are generated using the StyleGAN network; in the second stage, pattern element extraction is made based on eye-tracking technology; in the third stage, the designers carry out the design practice. As shown in Figure 1.

A. DATA PROCESSING

The dataset for importing model training requires that the phoenix and peony patterns have different textures to form a diversity of patterns. This study first collected patterns by interviewing inheritors of She intangible cultural heritage and visiting She Culture Museum, She Art Museum, etc. Secondly, relevant patterns were collected through literature review and online information acquisition; Finally, filter and organize the data. These images can be used as datasets for training. However, these images come from different sources and 512×512 have varying resolutions, so it is necessary to process these images and adjust their resolutions to uniformly to serve as the training set for StyleGAN.

B. STYLEGAN MODEL

The process of generating batik images is shown in Figure 2. In the process of generating batik images using StyleGAN, the system starts from an initial "imaginary material"-a latent vector that contains various image features but is mixed together. To enable independent adjustment of features such as color and texture, this material undergoes a processing stage akin to a "colorist", namely a fully connected network, which decomposes it into separate "material packages" to achieve decoupling between features. Subsequently, the generation process begins with an extremely small initial canvas. In each drawing round, the system first assigns a stylistic tone to the current canvas - derived from the previously decomposed independent material packages - and incorporates a touch of random variation to add liveliness.

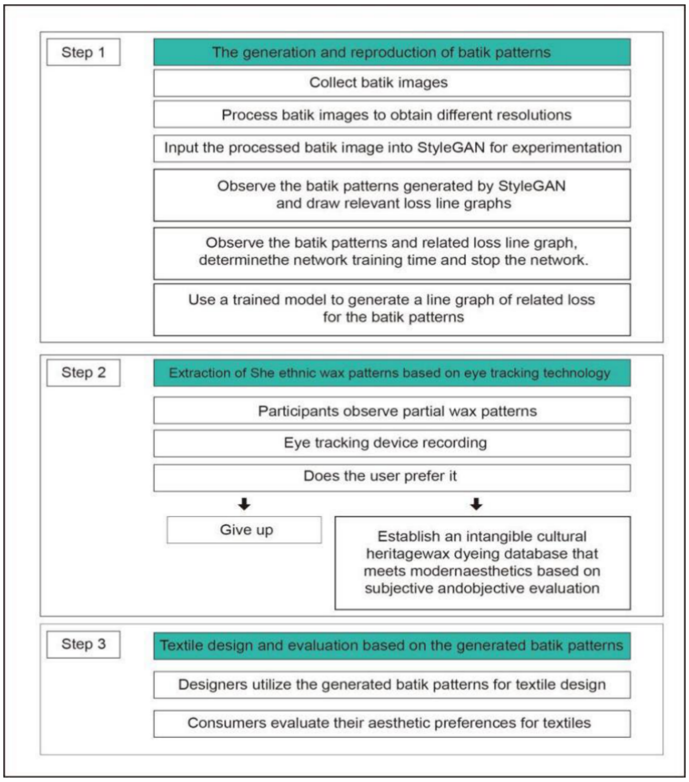


FIGURE 1. The research steps of this article

Then, through the "coloring" operation, which involves convolutional operations to add details, a slightly larger and clearer image is generated. In this way, the process of "assigning style and random variation - coloring - enlarging" is repeated, and the image gradually grows from a low-resolution sketch to a complete and delicate high-definition batik pattern. The generated image is then inputted into the "discriminator network" along with real batik images. The network analyzes the images layer by layer to determine their authenticity, and feeds the judgment results back to the generation network. The goal of the generation network is to make the generated image as realistic as possible, in order to "trick" the discriminator network; while the discriminator network strives to identify authenticity. The ongoing adversarial interplay between the two ultimately drives a gradual improvement in the quality of the generated images.

C. PATTERN EXTRACTION BASED ON EYE TRACKING TECHNOLOGY

The images generated based on StyleGAN ultimately formed a resource library of She ethnic phoenix and peony patterns. Subsequently, eye-tracking technology was employed to conduct preference experiments on the patterns of the participants, in order to avoid the subjectivity of designers extracting patterns and make the design of batik patterns more aesthetically pleasing to modern people. Eye tracking technology is an important method for studying visual cognition, which records the movement trajectory of each eye and the active area at the visual point through an eye tracking monitor. By analyzing multiple eye movement data such as Gaze Trail and Heat Map of the subjects, it can effectively reflect the objective evaluation of the design scheme by the subjects, providing objective data support for the selection of design schemes.

The experimental process of this study: Firstly, according to the images generated based on StyleGAN in the previous stage, a She ethnic batik pattern resource library is finally formed. Several sets of phoenix and peony patterns are randomly selected as experimental samples. Secondly, by allowing subjects to observe the sample for a certain period of time, eye movement data is recorded using an eye tracking device. Finally, a comprehensive analysis is conducted on the gaze duration, gaze trajectory, number of backtracking, eye skip activity, and other parameters observed by the subjects in different samples. The eye movement data is classified and statistically analyzed, and the key regions of interest and elements of interest for the subjects are obtained from it, in order to determine the key extraction objects for pattern elements in the samples.

D. OPTIMIZED DESIGN BY DESIGNERS

To verify the applicability of the new pattern in textile design, a design practice was conducted. Several professional designers were invited to engage in cultural and creative design practices featuring phoenix and peony patterns, such as designing handbags. Consumers were invited to assess the aesthetic acceptance of these designs on textiles.

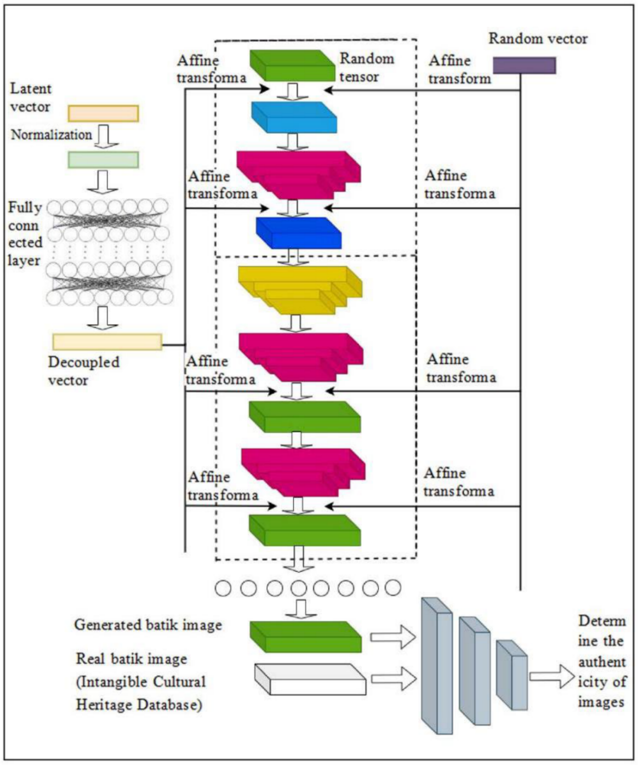


FIGURE 2. The generation process of batik patterns based on StyleGAN

IV. EXPERIMENTAL ANALYSIS OF BATIK IMAGE GENERATION BASED ON STYLEGAN

A. DATASET INTRODUCTION

In order to generate more realistic, aesthetically pleasing, and stylishly diverse batik images, some batik images with different patterns, textures, and colors were collected in this article. These batik images have different resolutions because they need to be input into the StyleGAN network as a dataset and cannot be directly used. Therefore, their resolutions need to be uniformly adjusted. In order to ensure the clarity of the 512×512 generated images and save training time, their clarity was adjusted to 512×512. Figure 3 shows some example images from the original batik image, indicating that the resolution of the original images is almost different. Figure 4 shows some examples of processed batik images, which have the same resolution 512×512 and do not affect the integrity of the original batik pattern, so they can be used as a dataset. Some batik images in the dataset have complex patterns, such as the comprehensive patterns of birds and plants or patterns with text. However, the generated batik images do not display these complex patterns, which may be due to the following reasons:

(1) The dataset is relatively small, and overfitting is prone to occur during the training process.

(2) There are very few batik images with complex patterns, and the generator cannot learn the data distribution of these batik patterns.

(3) This type of pattern has high complexity and difficulty in learning, especially for patterns of birds and plants, which require coordinated visuals and clear bird features. This is a challenging task for generating images from small datasets.

B. EXPERIMENTAL SETUP

The experimental environment of this article is a cloud environment on the AutoDL platform, using RTX 3090 (24GB) GPU, Intel (R) Xeon (R) Platinum 8358P CPU model, Ubuntu 18.04 operating system, Python version 3.8, PyTorch version 1.8.1, and Cuda version 11.1.

After 350 rounds of tick and 1400 rounds of kimg iterations in this experiment, we compared the generated batik images in terms of pattern integrity and style diversity, and analyzed the related convergence images. Finally, we chose a model with a tick of 300 and kimg of 1200 to generate images. The resolution of the generated image is 512×512.

C. ANALYSIS OF EXPERIMENTAL RESULTS

Figure 5 shows some examples of generating batik images in this article. By observing the original and generated batik images, the following conclusions can be drawn:

(1) The batik images generated in this experiment have similar textures to real batik images.

(2) The majority of the batik images generated in this experiment are patterns, which are quite similar to the real patterns.

(3) The colors of the batik images generated in this experiment are quite similar to those of the real batik

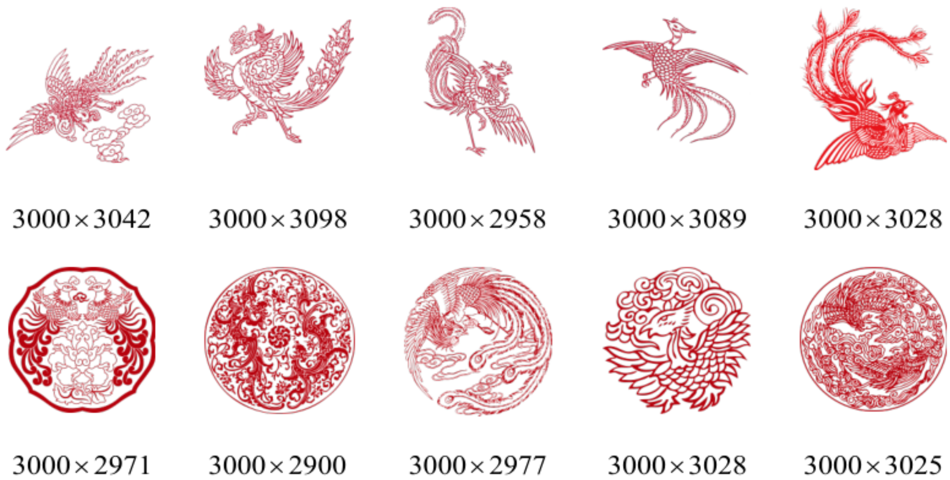


FIGURE 3. Example of a portion of the original batik image

FIGURE 4. Example of wax printing image with uniform resolution

images.

(4) The batik images generated in this experiment exhibit diversity in style.

Observing Figure 6, the following conclusions can be drawn:

(1) The curve tends to converge at 300 ticks (corresponding to 1200 kimg).

(2) At around 350 ticks, the curve suddenly drops, possibly due to overfitting caused by a small training set.

Table 1 shows the batik patterns generated by the StyleGAN network when the ticket is 150 (corresponding to 600 kimg), 200 (corresponding to 800 kimg), 250 (corresponding to 1000 kimg), 300 (corresponding to 1200 kimg), 350 (corresponding to 1400 kimg), and seeds are randomly selected as 350450550650.

By observing the images in Table 1, the following conclusions can be drawn:

(1) When the tick is less than 300, the pattern lines of the generated image are not delicate, the colors are not bright, and the pattern structure is relatively simple. As the training tick gradually increases, the pattern of the generated image gradually stabilizes, and the pattern details increase.

(2) When Tick>300, the patterns generated in the image are relatively similar, and the pattern structure is fuzzy, with weak overall integrity.

Based on Figure 6 and Table 1, a training model was selected with a tick of 300 and a kimg of 1200 to generate images in this experiment.

For the trained StyleGAN model, truncation_psi and seeds can be specified to generate images. The value of truncation_psi is between 0 and 1. The larger the value of truncation_psi, the greater the diversity of the generated image, and the greater the difference between images.

Table 2 shows the images generated by the StyleGAN model with a tick of 300 when seeds are randomly selected as 349, 461, 591, and 638, with different values of truncation_psi. In terms of visual effects, when the truncation_psi value is small, even if the input seeds are different, the generated images are relatively similar; As the truncation_psi value increases, the differences between

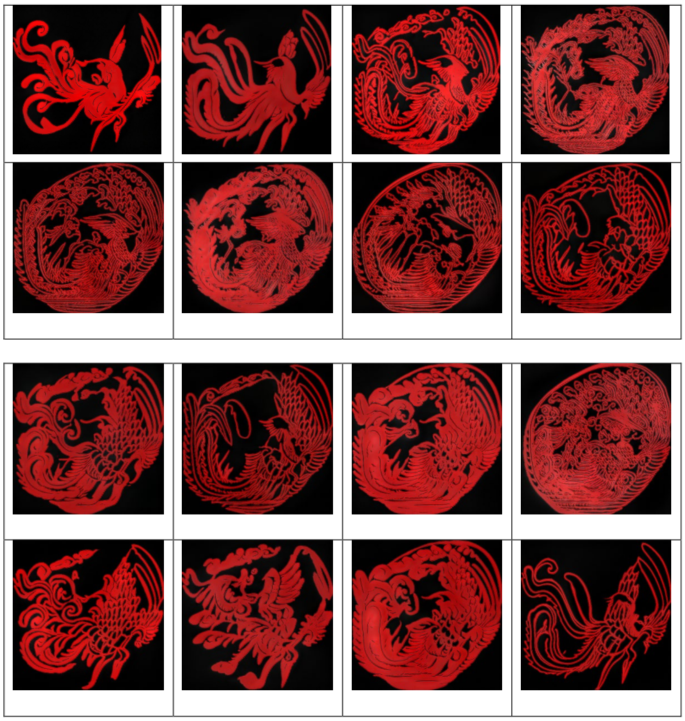


FIGURE 5. StyleGAN generated batik images

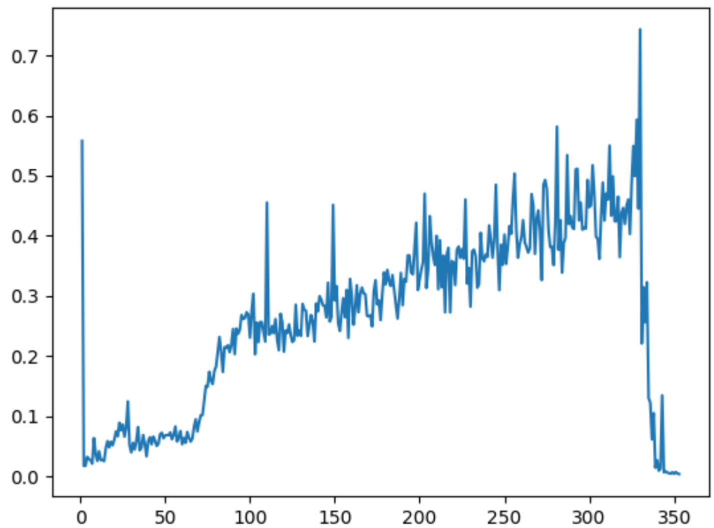


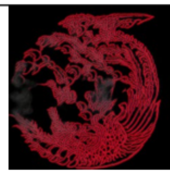
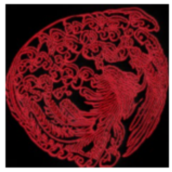
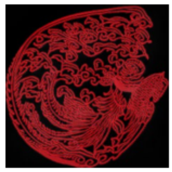
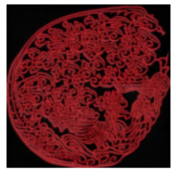
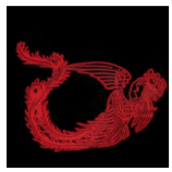
FIGURE 6. Curve graph of the discriminator discriminating generated images' authenticity

images corresponding to different seeds also become larger.

V. DESIGN INNOVATION OF WAX DYEING PATTERNS

The StyleGAN network can simulate the probability distribution of a dataset and generate images with similar features to the dataset images. In this article, images generated based on StyleGAN can form a She ethnic batik pattern resource library to assist designers in batik patterns design. In order to address the subjective issue of designers choosing batik patterns, eye movement data was combined with subjective evaluation in this study to extract the features of batik pattern elements, which were subsequently applied to the design of batik pattern. Firstly, remove some non-compliant or low-quality patterns from the She ethnic batik pattern resource library, and then randomly select three samples

TABLE 1. Comparison table of images generated by different ticks (kimg) when seeds are 349, 461, 591, and 638

	seeds			
tick(kimg)	349	461	591	638
150（600）				
200（800）				
250（1000）				
300（1200）				
350（1400）				

for eye movement experiment analysis. Now, consider the influencing factors from two aspects: experimental samples and subjects. The experimental samples include colors, playback time of individual samples, and visual residues of switching between samples; The subject section includes familiarity with the culture, gender, number of participants, age, cultural level, etc. The average time required for each participant to complete the entire experimental process is 15 minutes. Among them, the average time spent on explaining and debugging the equipment in the early stage is 8 minutes, the average time spent on conducting experiments is 2 minutes, and the feedback after the experiment is about 5 minutes. This study was approved by the Ethics Committee of Yiwu Industrial and Commercial College, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form.

A. ANALYSIS OF EYE MOVEMENT EXPERIMENT DATA

The eye movement experiment involved 30 participants, including 14 males and 16 females, aged between 19 and 30, with a majority holding a bachelor's degree. All subjects expressed a willingness to purchase cultural and creative products or had purchasing experience, and 43.4% were design professionals. The subjects' uncorrected or corrected visual acuity was above 1.0, and none suffered from color blindness or color deficiency.

In this experiment, research was conducted from two directions: one was based on the true reflection of eye movement data, and the other was based on the active evaluation of participants (conducting participant preference analysis on three patterns). Table 3 shows the results of fixation time within the region. For regions A, B, and C, the visual dwell time in different regions was calculated, and the average number of fixation points and average fixation time in the first fixation region and other regions were analyzed. By analyzing the proportion of gaze time in a region, it can be concluded that the larger the proportion, the higher the level of attention to this region. An analysis of the eye movement data from 30 participants revealed that participants pay more attention to regions B and C.

As shown in Figure 7, by analyzing the number of fixation points of the subjects in different regions, a heat map reflecting the degree of attention of the subjects in

TABLE 2. Comparison table of images generated by different truncation_psi with seeds of 375, 409, 432, and 455 and tick of 300

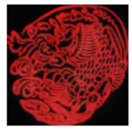
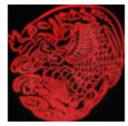
seeds	truncation_psi					
	0.1	0.3	0.5	0.7	0.9	1.0
375						
409						
432						
455						

TABLE 3. Results of eye movement experiment

Region	Number of viewers	Regional surface product proportion/%	Number of people staring at the area for the first time	Average number of fixation points	Average fixation duration/ms	Proportion of fixation time/%
A	30	33.3%	5	7.13	2635.86	15.2%
B	30	33.3%	14	20.93	8545.33	49.2%
C	30	33.4%	11	16.53	6192.60	35.6%

different regions can be obtained. Red, yellow, and green represent the degree of attention, with red indicating the highest degree of attention, followed by yellow, and green indicating the lowest. The graph is a superposition of all the heat maps of the subjects. The result showed that the attention of subjects in regions B and C is higher than that in region A.

From the analysis of gaze trajectory, as shown in Figure 8, the subjects first saw the phoenix pattern in the middle, then shifted their gaze to the lower left side, followed by the lower middle side, then returned to the left, revisited the middle, examined the right, and finally compared and observed between the three patterns. Through the trajectory map, it can be seen that the reading order of the subjects and the head of the phoenix pattern are the key regions that the subjects focus on. The phoenix tail in region C has a high level of attention.

B. OPTIMIZED DESIGN BY DESIGNERS

The designer used the preferred image B of the eye movement experiment object as the prototype, and then combined it with the key focus regions of image C for batik pattern design. The designer used PS/AI design software for drawing work. The specific work is as follows: First, conduct a quantitative assessment of visual attention on various patterns in the regions of images B and C, and calculate the visual weight and attention frequency of each pattern. Based on this, determine the priority order. Then, accurately extract the core visual features of the phoenix crown and peony in region B, and arrange them in that order. Meanwhile, for region C, select the phoenix head and tail patterns with high attention rankings for matching application. During the precise extraction and visual reconstruction of the above elements, professional designers used the smooth curve tools in PS and AI software to conduct fine tracing and vector construction on the contour lines and detailed textures of the phoenix head, peony, and phoenix tail, ultimately generating standardized detailed images. As shown in Figure 9, the designer processed the drawn phoenix pattern into a rotating and dancing dynamic shape and integrated it with the peony element into a circular composition, achieving harmonious coexistence between the two.

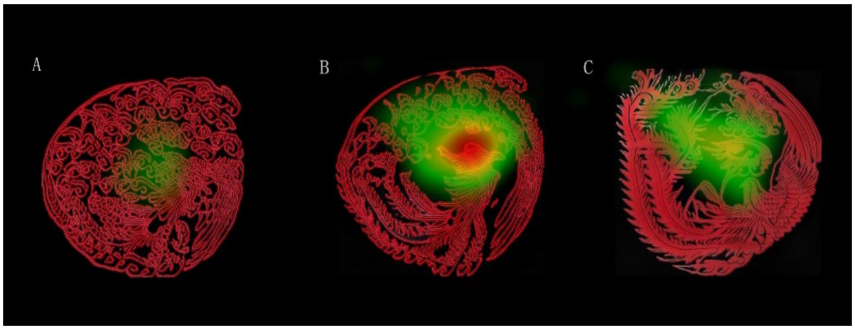


FIGURE 7. Heat map

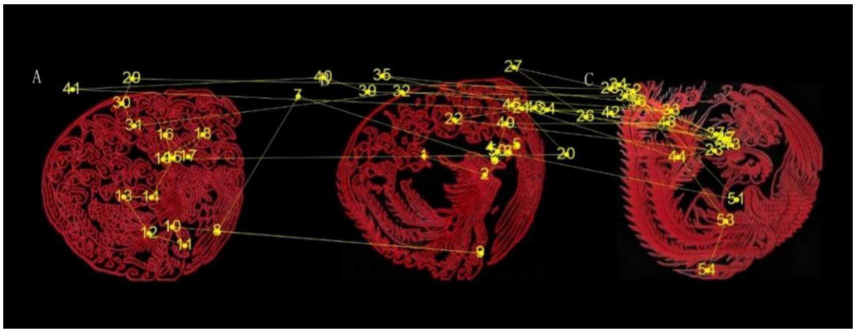


FIGURE 8. Gazing trajectory map

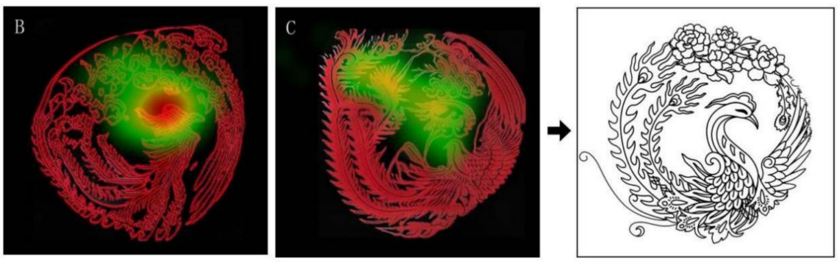


FIGURE 9. Optimized design by the designer

C. CONSUMERS' AESTHETIC PREFERENCE EVALUATION OF BATIK PATTERN TEXTILES

In this section, the aesthetic preferences for four batik patterned textiles were evaluated, as shown in Figure

10. The test was conducted in the form of a questionnaire, with a total of 157 participants, including 50 males and 107 females. The participants were mainly young people aged 18-25, with a higher proportion of females. Their educational backgrounds were mainly college and undergraduate degrees, and their occupations were mostly e-commerce practitioners. Their professional backgrounds were mainly in art design and e-commerce. Cronbach's Alpha is a widely used reliability analysis method, primarily employed to assess the internal consistency and reliability level of data. The results of the reliability test for the current survey data indicate a Cronbach's Alpha coefficient of 0.848, suggesting that the data reliability falls within an ideal and acceptable range. The experimental results are shown in Figure 11. The credibility of four batik pattern textiles averaged at 3.92, with the highest score being 4.07. This means that the generated new batik patterns can meet the aesthetic preferences of users.

VI. CONCLUSION

As a cornerstone of China's traditional textile printing and dyeing industry, batik utilizes specialized resist-dyeing techniques to apply intricate motifs onto various fabric substrates and apparel. These batik patterns emerge from the rhythms of daily life and serve as a material record of the textile craftsmanship, aesthetic values, and socio-economic standards of their respective eras. They have great historical and aesthetic research value, so inheriting and developing batik patterns has great historical and aesthetic significance. In this article, batik patterns of the She ethnic group are mainly designed.

The main work of this article is as follows: Firstly, traditional handmade design methods require designers to have a high level of artistic skills, including painting skills and corresponding historical and cultural knowledge. StyleGAN

FIGURE 10. Four textiles with batik patterns

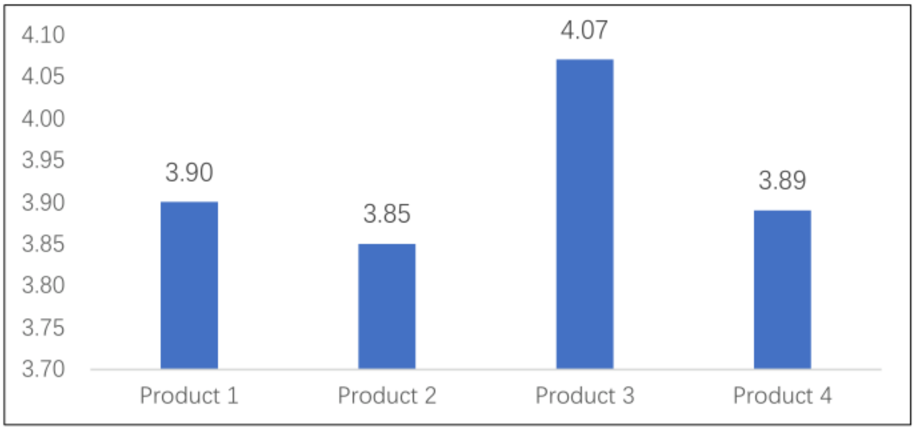


FIGURE 11. Evaluation results of aesthetic preference for batik textiles

is employed in this article to generate new batik patterns, including two types of patterns, phoenix and peony. The results show that StyleGAN can learn the data features of existing batik patterns, and the generated batik patterns combine the shape features of phoenix and peony patterns, achieving good results in color, texture, and diversity. They not only retain the aesthetic features of the original batik patterns, but also integrate and innovate to maintain a high degree of diversity. Next, visually attractive images are selected from the generated images for eye movement experiments, and then data analysis is performed from three dimensions: gaze duration, heatmap distribution, and gaze trajectory within the region to determine which regions in the selected images are more attractive. Once again, the designer fuses the attractive features of phoenix and peony patterns together to form the final creative pattern. Finally, to verify the applicability of the new pattern in textile design, cultural and creative design practices are conducted with the theme of phoenix and peony patterns, such as designing handbags. Based on the survey results, it can be concluded that these designs meet the aesthetic expectations of the respondents and demonstrate their application value in textile design and textile decoration.

AUTHOR CONTRIBUTIONS

Conceptualization –Yanfei Liu and Zixing Li; methodology – Yanfei Liu and Zixing Li; investigation – Yanfei Liu and Zixing Li; writing-original draft preparation – Yanfei Liu and Zixing Li. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

FUNDING

This research was supported by, [Jinhua Municipal Science and Technology Bureau] (Grant number 2022-4-306)

Project Title: Research on the Extraction and Design Application of She Ethnic Cultural Elements Based on Eye-tracking Technology.

HUMAN RESEARCH SUBJECTS

This study was approved by the Ethics Committee of Yiwu Industrial and Commercial College, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form.

ACKNOWLEDGEMENTS

Not applicable.

REFERENCES

[1] M. Vecco, "A definition of cultural heritage: From the tangible to the intangible," Journal of Cultural Heritage, vol. 11, no. 3, pp. 321-324, 2010, doi: 10.1016/j.culher.2010.01.006.

[2] Z. Lei, "From Folk Batik Handicraft to Modern Batik Painting Art," Art Observation, no. 2, pp. 150-151, 2019.

[3] Q. Li, "Design Research on Virtual Reality Technology in the Inheritance of Non-material Cultural Heritage," Packaging Engineering, vol. 44, pp. 337-340, 2023.

[4] Y. Ma and L. Zhang, "Inheritance and Protection of Non-material Cultural Batik Skills from a Digital Perspective," Cotton Textile Technology, vol. 51, no. 8, p. 96, 2023.

[5] Z. Li, "Digital Pattern Design of National-level "Non-heritage" Sichuan Gongxian Miao Batik," Shanghai Textile Science & Technology, vol. 48, no. 9, p. 109, 2020, doi: 10.16549/j.cnki.issn.1001-2044.2020.09.070.

[6] S. Hu, Q. Jia, Y. Q. Wang, L. L. Dong, and Y. M. Luo, "Research on the Redesign of Traditional Cultural Symbols Based on Eye Movement Experiments and Extension Semantics," Decoration, no. 8, pp. 88-91, 2021.

[7] L. Ye, S. Yang, X. Zhou, and Y. Lin, "Supporting traditional handicrafts teaching through eye movement technology," International Journal of Technology and Design Education, vol. 33, no. 3, pp. 981-1005, 2023, doi: 10.1007/s10798-022-09748-z.

[8] N. Zhang, Q. Yang, J. Wang, Y. Chen, and J. Zhang, "Extraction and Application of Design Elements of Miao Embroidery under Eye Movement Analysis," Packaging Engineering, vol. 41, pp. 248-254, 2020.

[9] F. Liu, J. Kang, Y. Wu, D. Yang, and Q. Meng, "What do we visually focus on in a World Heritage Site? A case study in the Historic Centre of Prague," Humanities and Social Sciences Communications, vol. 9, pp. 400, 2022, doi: 10.1057/s41599-022-01411-1.

[10] D. Gülhan, S. Durant, and J. M. Zanker, "Similarity of gaze patterns across physical and virtual versions of an installation artwork," Scientific Reports, vol. 11, 18913, 2021, doi: 10.1038/s41598-021-91904-x.

[11] Y. Zhu and C. Deng, "Research on the Cultural Image Genes of Liao Porcelain Based on Psychological and Physiological Measurements," Journal of Computer-Aided Design & Computer Graphics, vol. 32, no. 7, pp. 1183-1191, 2020.

[12] Y. Yu and P. Deng, "The Application of Perlin Noise in Batik Digitization," Journal of Yunnan Minzu University (Natural Sciences Edition), vol. 29, no. 6, pp. 607-613, 2020.

[13] Y. Wu and H. Zhang, "Image style recognition and intelligent design of oiled paper bamboo umbrella based on deep learning," Computer-Aided Design and Applications, vol. 19, no. 1, pp. 76-90, 2022, doi: 10.14733/cadaps.2022.76-90.

[14] Y. Cui, J. Yang, F. Li, and P. Yue, "Research on Intelligent Auxiliary Design of Magnet Kiln Decorative Patterns," Packaging Engineering, vol. 44, no. 16, pp. 1-9, 2023, doi: 10.19554/j.cnki.1001-3563.2023.16.001.

[15] M. Arjovsky, S. Chintala, and L. Botou, "Wasserstein generative adversarial networks," in Precup D, Teh YW, editors. Proceedings of the 34th International Conference on Machine Learning, 2017 Aug 6-11, Sydney, Australia. PMLR, 2017, pp. 214-223, [Online]. Available: https://proceedings.mlr.press/v70/arjovsky17a.html.

[16] M. Mirza and S. Osindero, "Conditional generative adversarial nets," arXiv preprint arXiv:1411.1784, 2014, doi: 10.48550/arXiv.1411.1784, [Online]. Available: https://arxiv.org/abs/1411.1784.

[17] H. Zhang, I. Goodfellow, D. Metaxas, and A. Odena, "Self-attention generative adversarial networks," in Chaudhuri K, Salakhutdinov R, editors. Proceedings of the 36th International Conference on Machine Learning, 2019 Jun 9-15, Long Beach, CA, USA. PMLR, 2019, pp. 7354-7363.

[18] X. X. Meng, J. W. Li, L. W. Han, and Y. P. Zhu, "Research on Handwritten Chinese Character Image Generation Based on DCGAN," Modern Computer, vol. 29, no. 20, pp. 29-34, 2023, doi: 10.3969/j.issn.1007-1423.2023.20.005.

[19] Y. Liu, G. Guo, Z. Qi, Z. Li, and F. Sun, "Research on Embroidery Image Restoration Based on Improved DCGAN," Laser & Opto-electronics Progress, vol. 60, no. 20, pp. 1-11, 2024, doi: 10.3788/LOP223060.

[20] T. Wang, Z. Ma, and L. Yang, "Creativity and sustainable design of wickerwork handicraft patterns based on artificial intelligence," Sustainability, vol. 15, p. 1574, 2023.

[21] L. Q. Yang and X. Y. Liu, "Worshipping the Phoenix as the Supreme: The Aesthetic Characteristics of the Phoenix Pattern in Fuding She Ethnic Women's Clothing," Journal of Donghua University (Social Science Edition), vol. 23, no. 2, pp. 34-40, 2023, doi: 10.19883/j.1009-9034.2022.0537.