Digital design of regional characteristic apparel pattern driven by GAN

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HAN CHEN
LEI SHEN
XIYING ZHANG
XIANGFANG REN
MINGMING WANG
XUE MIN
XUE LI

ABSTRACT – REZUMAT

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In the links of apparel product development and production, apparel pattern design cannot reduce its marginal cost through economies of scale because of its creative characteristics. With the world entering the era of industry 4.0, machine learning can provide services for apparel design. This research takes the Chinese characteristic tachisme pattern as the research object and puts forward a new design method of regional characteristic apparel pattern driven by Generative Adversarial Networks (GAN). Firstly, the main framework based on GAN including discrimination and generation modules is established. Aiming at the training difficulties of regional characteristic apparel pattern sample situation with small quantity and disordered specification, the image self-amplification and normalization pre-processing module is added to the model. Secondly, by adding the Batch Normalization mechanism, Leaky ReLU and RMSProp algorithm, the problems of gradient disappearance and overfitting in the experiment are solved, and the convergence speed of the model is improved. Finally, the HSV colour model algorithm is introduced into the loss function to indicate the training process, so that the artistic expression characteristics of the generated results are closer to the human visual perception experience. Through index evaluation comparison, result authenticity investigation and product design practice, we prove the superiority and practicality of the proposed method in this paper. The new design method theoretically solves the scale economy dilemma of the previous apparel pattern design methods and provides reference ideas for more application scenarios currently trapped in the real-time presentation of design results.

Keywords: *apparel pattern, digitalization, design efficiency, generative adversarial network, machine learning, scale economy, regional characteristic*

Design digital al modelului de îmbrăcăminte caracteristic regional prin GAN

În relația dintre dezvoltarea și producția de produse de îmbrăcăminte, designul modelelor de îmbrăcăminte nu își poate reduce costul marginal prin economii de scară din cauza caracteristicilor sale creative. Odată cu intrarea lumii în era industriei 4.0, învățarea automată poate oferi servicii pentru designul de îmbrăcăminte. Această cercetare are ca obiect de cercetare modelul tașism caracteristic chinezesc și propune o nouă metodă de proiectare a modelului de îmbrăcăminte caracteristic regional prin Rețelele Adversare Generative (GAN). În primul rând, se stabilește cadrul principal bazat pe GAN, inclusiv modulele de discriminare și generare. Având în vedere dificultățile de prelucrare ale probei de model de îmbrăcăminte caracteristice regionale cu dimensiuni mici și specificații dezordonate, modulul de pre-procesare și autoamplificare a imaginii este adăugat la model. În al doilea rând, prin adăugarea mecanismului de normalizare a loturilor, a algoritmului Leaky ReLU și RMSProp, se rezolvă problemele de dispariție a gradientului și supraadaptarea în experiment, iar viteza de convergență a modelului este îmbunătățită. În cele din urmă, algoritmul modelului de culoare HSV este introdus pentru a indica procesul de prelucrare, astfel încât caracteristicile de expresie artistică a rezultatelor generate să fie mai apropiate de experiența de percepție vizuală umană. Prin compararea evaluării indicilor, investigarea autenticității rezultatelor și practica de proiectare a produsului, demonstrăm superioritatea și caracterul practic al metodei propuse în această lucrare. Noua metodă de proiectare rezolvă teoretic dilema economiei de scară a metodelor anterioare de proiectare a modelelor de îmbrăcăminte și oferă idei de referință pentru mai multe scenarii de aplicație blocate în prezent în prezentarea în timp real a rezultatelor designului.

Cuvinte-cheie*: model de îmbrăcăminte, digitalizare, eficiența designului, rețea adversară generativă, învățare automată, economie de scară, caracteristică regională*

INTRODUCTION

Along with the economic development of various countries to the middle and high-income levels, the great increase in production element costs and other factors have led to the gradual loss of the price advantage in the apparel industry. Some traditional apparel producing countries are trying to change their position in the value chain of the international apparel industry from low-end manufacture to high-end research and design [1]. At the same time, in the global cultural convergence, the world apparel industry derives a popular phenomenon of regional apparel characteristics [2]. Diversified regional characteristic apparel style has become an obvious global fashion trend, replacing the previous relatively single mainstream fashion style. This provides opportunities for the upgrading and transformation of the apparel industry in more countries in the world and also puts forward higher requirements for the design method of regional characteristic apparel pattern.

Most of the traditional apparel pattern design methods are designers creating patterns with the help of computer-aided software [3]. Such a design method relies too much on manpower and cannot reduce the marginal cost. In addition to those shortcomings, traditional design methods also have some problems, such as low efficiency, poor controllability, low fault tolerance, unable to present in real-time and so on. Therefore, how to match the current high demands of the apparel industry by upgrading and transforming through the new design method has become an urgent research topic [4].

With the development of machine learning generation technology and the improvement of computing power, it is possible for computers to assist and replace human beings to complete the creative behaviour related to apparel design. Phillip Isola proposed an innovative conditional advertising network [5]. Human beings only need to provide the line draft of the apparel, and this network algorithm can quickly design the matching apparel rendering effect. The DiscoGAN network built by Taeksoo Kim based on GAN realizes the learning of cross-domain relationships without label or pairing, and successfully transmits the style patterns on the handbag to the shoes across domains, thus realizing the serial dress design by machine algorithm [6]. Donggeun Yoo presented an image-conditional image generation model by introducing a novel domain-discriminator [7]. The model successfully generated a piece of clothing from an input image of a dressed person. Although machine learning generation methods currently have some applications in the direction of apparel design, it is rare to apply the methods, especially the GAN theory to regional characteristic apparel pattern design.

MATERIAL AND METHODS

Material

In this study, the Chinese characteristic tachisme pattern is selected as the research object. As one of the important performance techniques of Chinese painting, tachisme has rich and changeable artistic expression, profound cultural connotation and oriental symbol image [8]. Different proportions of water and colour are mixed to get rich colour layers. Together with the blank layout, it shows the dynamic picture sense and lively life image, which is very suitable for textiles made of various fabrics.

Considering that solving the problem of regional characteristic apparel patterns with small samples and different specifications is also one of the important research directions of this paper, we collected 361 pieces of tachisme apparel patterns with different sizes and quality specifications as a small sample data set. The model is optimized with the addition of a pattern self-processing module, so the training samples material does not need to be prepared manually. The experiment environment for the study is Ubuntu 16.04 LTS, Intel Xeon(R) CPU E5-2637 V4.5, GeForce RTX 3090 * 4 / PCIe / 24 GB video Cards, 16g * 4 / DDR4 / 3200MHz RAM. The network is built with the Python 3.7 computer processing language.

Methods

Machine learning generation model

With the advent of the AI era, more and more scholars devote themselves to the research of machine learning generation model and apply it to the generation of images, audio, video and other objects [9]. Most of the machine learning generation models are based on the maximum likelihood estimation principle. Based on this principle, the generation models can be divided into explicit density model and implicit density model [10].

The explicit density model is based on an explicit density function, which is easy to calculate. It can be divided into the approximate density estimation model and the accurate density estimation model according to the calculation accuracy. Approximate density estimation models can be classified into the variational approximate model and MCMC (Markov Chain Monte Carlo) approximate model according to the approximate methods. Accurate density estimation models can be divided into fully visible belief network and variable models according to their definition methods. Compared with the explicit density generation model, the implicit density generation model does not need to define an explicit density function for training but realizes the training through an indirect interaction model from sampling. The generation models based on implicit density include GSN (Generative Stochastic Networks) and GAN. The classification relationships between different classes of generative models are shown in figure 1. Because of the differences in principles and training mechanisms, the performance of various classes of generative models and the kinds of data objects they are good at handling differ [11]. We summarize the advantages and disadvantages of different generation models, as shown in table 1.

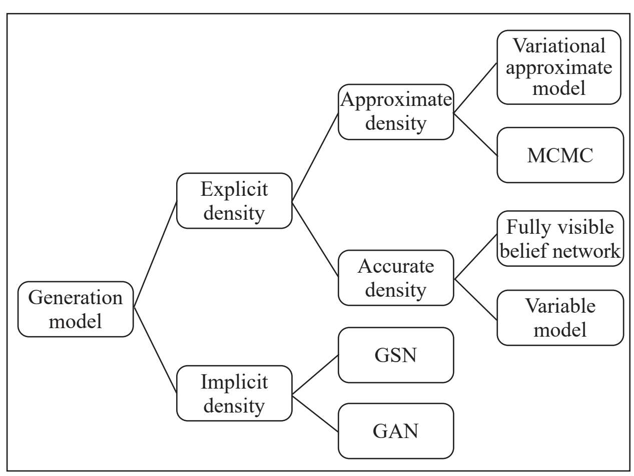


Fig. 1. Classification of generation models

Table 1

ADVANTAGES AND DISADVANTAGES OF GENERATION MODELS		
Categories of models	**Advantage**	**Disadvantage**
Variational approximate	The quality of likelihood acquisition is high	The model is difficult to optimize and the probability of low-quality results is high
MCMC	The model is easy to converge	The convergence time of the model is long
Fully visible belief network	It is suitable for processing continuous and discrete data, and the training process is relatively stable	It takes a long time to generate the result and the quality of the generated image is low
Variable model	It is convenient to optimize the algorithm design directly on the training data	It is difficult to find the corresponding reversible mapping change
GSN	Suitable for approximate partition function and learning	It is difficult to deal with large sample data in high dimensional space
GAN	The quality of the generated results is high, and the model optimization design is flexible	The interpretability of the generation process is low. It is difficult to find a comprehensive evaluation index of the model performance

GAN

GAN is an unsupervised machine learning model which is trained by an adversary proposed by Ian Goodfellow in 2014 [12]. GAN generates high-quality samples with the unique idea of zero-sum game and adversary training, which has better feature learning and expression performance than other machine learning generation models [13]. The core units of GAN are generator and discriminator. The generator generates fake samples from the noise distribution for the purpose of deceiving the discriminator. The discriminator discriminates the authenticity of the generated samples. There is a zero-sum game for two relationships between the roles of generator and discriminator.

GAN can generate samples by sampling noise once, which is different from most generating models that generate samples by serial mode. GAN does not need a variational lower bound to generate the result directly. Therefore, the image quality generated by the GAN is generally better than other types of generation models. However, there are still some challenges to be solved, such as the low interpretability of the generation process, the difficulty to calibrate the comprehensive and objective evaluation index of the model performance, and the instability in the training process.

Model building

Based on the GAN, the main framework of the apparel pattern design model composed of a generator and discriminator is built, as shown in figure 2. The generator simulates human apparel pattern designers to create tachisme apparel patterns through training. The discriminator learns the artistic expression characteristics of tachisme apparel pattern through training and simulates human art critic to judge whether the input pattern is designed by human or by generation module.

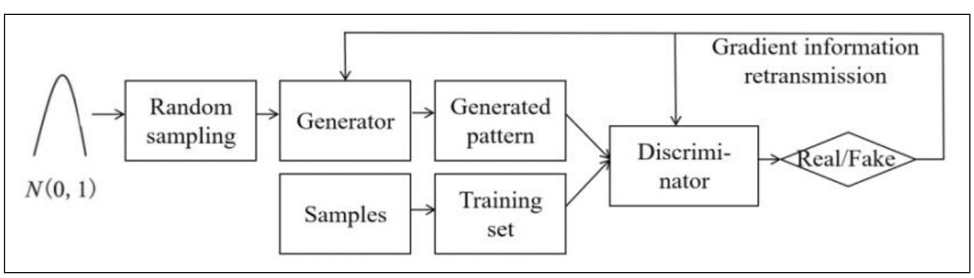


Fig. 2. Main model of pattern digital design

The number and quality of training samples are required for the training of GAN. Regional characteristic apparel patterns are mostly artistic creation [14]. This is different from the real photos of the research objects in other popular application directions of GAN. In the sample collection of the training set, there are a few original training samples, and the image quality and size specifications are not unified. In order to improve the trainability of regional characteristic apparel patterns and the automation of the overall model, we built the module using an expansion standardization algorithm before the training set as input to the discriminator. This module can automatically enlarge the number and standardize the specification of the input training set image in the present appropriate range, which highly enhances the trainability of the sample set, and significantly decreases manual sample pre-processing effort. Specifically, we prepared 361 pieces of tachisme art design patterns in different specifications, which belongs to a typical small sample of regional characteristic pattern training data set. The image self-amplification normalization pre-processing module can effectively enlarge the number of samples to 821 by randomly flipping the image and randomly changing the brightness and contrast. After that, the module unifies the quality and size of the image automatically. This method also effectively reduces the negative impact of sample amplification random transformation.

For reducing the slow convergence and gradient dispersion phenomenon of the model in the experiments, which happen to vary degrees during learning, Batch Normalization and Leaky ReLU are added to optimize the parameters of the algorithm. The Batch Normalization mechanism avoids gradient disappearance by pulling hidden layer neurons from a non-normal allocation back to a relatively regular allocation [15]. By giving a gradient that is not zero to each negative number, Leaky ReLU can significantly speed up the learning speed of the model and shorten the convergence process [16].

There are two deficiencies in the original loss function of the GAN: it is easy to collapse the pattern, which can lead to the phenomenon of homogenization of the resulting image; its instability will lead to the failure to indicate the training process to a certain extent, making the training unable to converge [17]. Wasserstein loss function is proposed to solve the above problems by leaps and bounds, so it is used by many mainstream GAN models [18]. In order to ensure the performance and stability of the model, the Wasserstein loss function is used instead of the original function to optimize the model in this research.

In addition to the consideration of model stability, we make structural changes to the model loss function for the special artistic expression characteristics of tachisme patterns. The key artistic expression feature of the tachisme pattern is the rich colour layers after the mixing of water and colour. In order to make the output of the model closer to people's intuitive experience of tachisme art, we introduce the concept of HSV (Hue, Saturation, Value) colour model. Compared with RGB (Red, Green, Blue) colour standard which is widely used, the HSV colour model pays more attention to users' visual perception of colour and is closer to people's perception experience of colour. Therefore, it is more suitable for a quantitative description of tachisme apparel patterns with rich colour layers of visual performance.

Finally, we use Wasserstein and HSV colour space Euclidean distance to measure the quality of the generated image. In the HSV cone with hypotenuse length R, bottom circle radius R and height h, the coordinate axis is established with the ground circle centre as the origin and $H=0$ as the positive direction of X axis [19]. Then the three-dimensional coordinates (x, y, z) of the point with colour value (H, S, V) are:

$$\begin{aligned} x &= r * V * S * \cos H \\ y &= r * V * S * \sin H \\ z &= h * (1 - V) \end{aligned} \tag{1}$$

In this case, the Euclidean distance D used to measure the similarity of two images in HSV space is calculated as follows:

$$D = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2 + (z_1 - z_2)^2} \tag{2}$$

We combine these two measures and give them 0.5 weight to form the loss function of the model:

$$\text{Loss} = 0.5 * \text{Wasserstein loss} + 0.5 * \text{HSV loss} \tag{3}$$

Figure 3 shows the structure of the model after optimization design. The model will use the output and error calculated by the discriminant module to train and generate the module weight. The discriminators are learned independently, so we set the ranges of the discriminators to be non-trained so that we can ensure that only the ranges of the generators can be trained to be upgraded. The change of trainability in the weight of the discriminant module is only effective when training the whole model, but not when training the discriminant module alone. The overall network randomly samples the noise and inputs them to the generator for pattern creation. The created pattern is fed back to the discriminator as input and is dichotomized as real or fake as the output. The model uses a user-defined weighted loss function including Wasserstein loss and HSV colour space to optimize training with RMSProp in the 0.00005 training value.

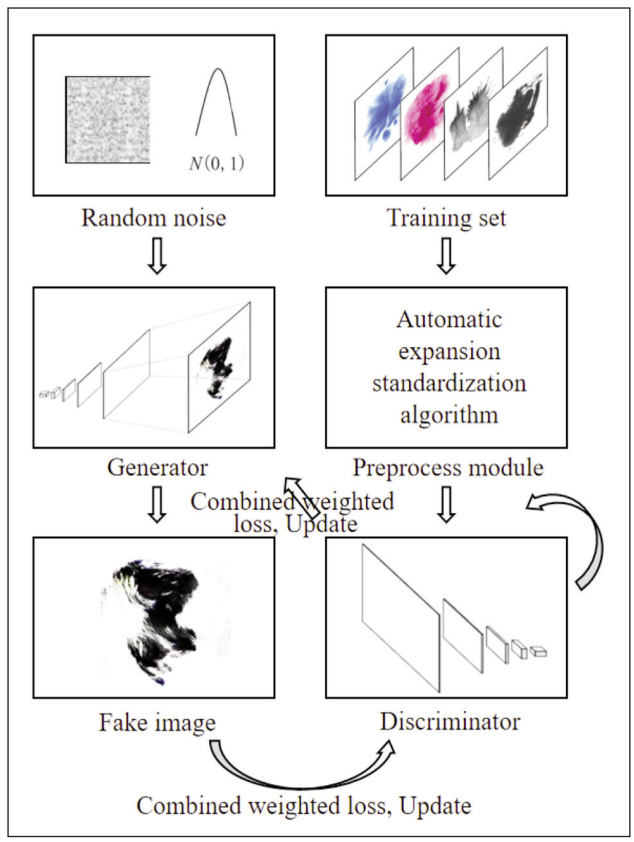


Fig. 3. Model frame diagram

The discrimination module and the generation module are the core parts of the whole model. Model optimization design such as Batch Normalization and Leaky ReLU is also reflected in these two parts. The specific structure of the discrimination module is shown in table 2. The input of this module is the 256*256 image processed by the pre-processing module, and the output is the score of the authenticity of the image. The module subsamples in Batch Normalization, Leaky ReLU of 0.2 value and convolution layer of 2*2 step size. The discriminant module

Table 2

HIERARCHICAL STRUCTURE OF DISCRIMINATE MODULE		
Layer	**Output Shape**	**Param**
Conv2D	(None, 128, 128, 64)	4864
LeakyReLU	(None, 128, 128, 64)	0
Conv2D	(None, 64, 64, 128)	204928
BatchNormalization	(None, 64, 64, 128)	512
LeakyReLU	(None, 64, 64, 128)	0
Conv2D	(None, 32, 32, 256)	819456
BatchNormalization	(None, 32, 32, 256)	1024
LeakyReLU	(None, 32, 32, 256)	0
Conv2D	(None, 16, 16, 512)	3277312
BatchNormalization	(None, 16, 16, 512)	2048
LeakyReLU	(None, 16, 16, 512)	0
Flatten	(None, 131072)	0
Dense	(None, 1)	131073

Table 3

HIERARCHICAL STRUCTURE OF GENERATE MODULES		
Layer	**Output Shape**	**Param**
Dense	(None, 1, 1, 131072)	13238272
Reshape	(None, 16, 16, 512)	0
BatchNormalization	(None, 16, 16, 512)	2048
ReLU	(None, 16, 16, 512)	0
Conv2DTranspose	(None, 32, 32, 256)	3277056
BatchNormalization	(None, 32, 32, 256)	1024
ReLU	(None, 32, 32, 256)	0
Conv2DTranspose	(None, 64, 64, 128)	819328
BatchNormalization	(None, 64, 64, 128)	512
ReLU	(None, 64, 64, 128)	0
Conv2DTranspose	(None, 128, 128, 64)	204864
BatchNormalization	(None, 128, 128, 64)	256
ReLU	-	0
(None, 128, 128, 64)	-	4803
(None, 256, 256, 3)	(None, 256, 256, 3)	0

uses the combined weighted loss function of Wasserstein loss and HSV colour space to optimize under the random gradient descent of RMSProp with a learning rate of 0.00005. The total parameters of the model are 4441217.

The specific structure of the generation module is shown in table 3. The input of the module is random noise and the output is a single 256*256 image. The module uses Leaky ReLU, Batch Normalization and transposed convolution layer with a step size of 2*2 to upsample the data. The model uses tanh as the activation function in the output layer. The generation module also uses the combined weighted loss function of Wasserstein loss and HSV colour space to optimize under the random gradient descent of RMSprop with a learning rate of 0.00005. The total parameters of the model are 17548163.

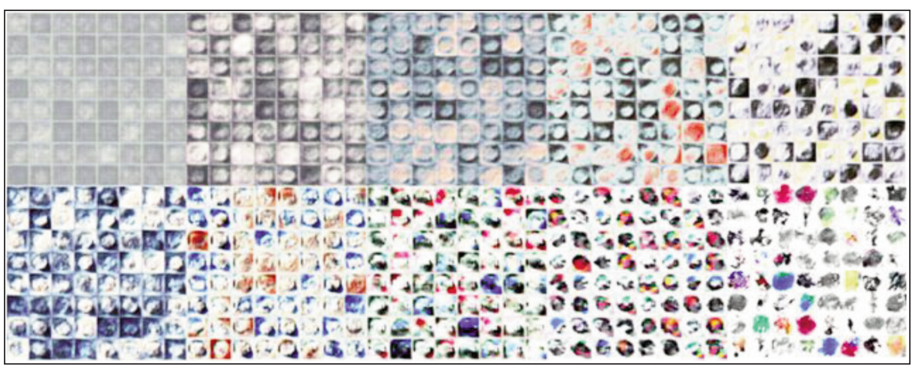


Fig. 4. The output pattern of generate module during training

RESULTS AND DISCUSSION

Model training

The model continuously creates tachisme patterns that are closer to the real human designer's work through unsupervised self-learning under the direction of the loss function. Figure 4 shows the generated patterns we pulled out at different points in the model learning process.

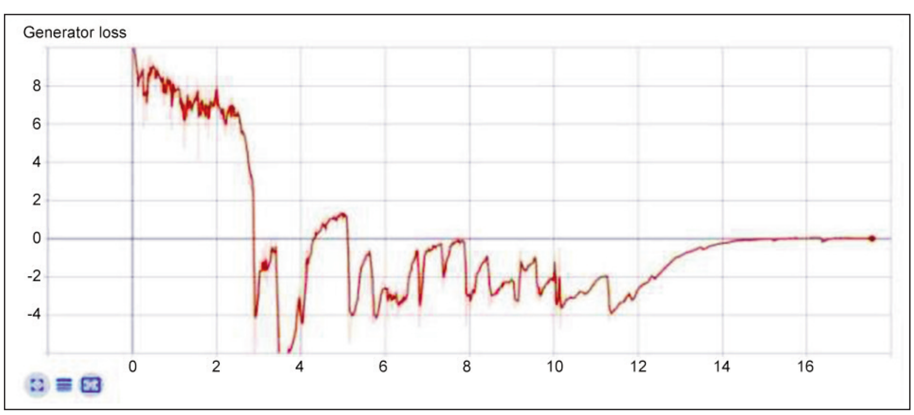


Fig. 5. Change of loss function

The whole learning process lasted for about 16,000 cycles and took about 15 hours, and the final loss function was close to 0, as shown in figure 5.

Comparative experiment and design application

Compared with the previous apparel pattern design method based on designer creation, the method of this study exhibits significant productivity. In comparison

Table 4

THE COMPARISON EXPERIMENTAL RESULTS BETWEEN THE TYPICAL MODEL THE AND MODEL IN THIS PAPER					
Model	**Training time**	**Generation time of 10000 images**	**IS**	**FID**	**MS-SSIM**
Model in this study	15h	72.12s	3.13	24.7	0.23
Primitive GAN	24h	73.63s	2.34	39.6	0.39
DCGAN	18h	78.98s	2.493	27.1	0.27

with other non-adversarial generative algorithm models, the quality and time-consuming of the generated pattern of this research model are also significantly improved [20]. This is related to the principle and mechanism of GAN, the core theoretical framework of this research model. Therefore, we mainly select the comparison experimental group of the model proposed in this study among the models that also use GAN as the core construct. Through the analysis and experiment of other mainstream models based on GAN, we choose the primitive GAN and DCGAN as the comparison experimental group. We chose conventional measures including training time and 10,000 pattern creation time to evaluate the network model. We also selected IS (Inception Score), FID (Frechet Inception Distance) and MS-SSIM (Multi-Scale Structural Similarity Index) to evaluate the ability of the network model to process samples and the quality of the output results. IS is the value that is more often used to quantitatively evaluate the quality and richness of the results generated by GAN [21]. Is needs to use Google pre trained perception net to calculate the score value. The higher the IS score, the higher the diversity and quality of the image. FID is an index to measure the model performance by the distance between the generated data distribution and the real data distribution [22]. FID score is widely used to evaluate the performance of different models, it performs well in terms of discriminability, robustness and efficiency [23]. Martin Heusel have shown that FID is more consistent with the noise level than the Inception Score in his research [22]. The smaller the FID value is, the better the result is. MS-SSIM is described by many scholars as the most successful method for quantitatively evaluating image similarity by attempting to predict human perceptual similarity judgements [24, 25]. MS-SSIM is a multi-scale variant of a well-characterized perceptual similarity metric that attempts to discount aspects of an image that are not important for human perception [26]. The lower the MS-SSIM value (between 0 and 1), the higher the image diversity. The results of comparison experiment data are shown in table 4. It can be seen that compared with the primitive GAN and DCGAN, the model proposed in this paper shows better performance in dealing with the research object of regional characteristic tachisme apparel pattern.

Considering the subjectivity of artistic creation in apparel pattern design, in order to test the authenticity of design results and the judgment ability of the model discriminator, we set up a personnel discrimination test. There are 60 respondents in this experiment. Among them, 40 respondents are engaged in clothing-related work and have different degrees of clothing-related professional and educational backgrounds. Another 20 respondents were engaged in work unrelated to clothing. All 60 respondents were from Binhu District, Wuxi City, China. The respondents' choice of gender and age is random. The gender and age distribution of 60 respondents is shown in table 5. A total of 50 tachisme apparel patterns were distributed to the interviewees, which were

Table 5

GENDER AND AGE DISTRIBUTION OF RESPONDENTS				
Age range	**Number of men**	**Number of women**	**Number of people**	**Proportion of people number**
11–20	4	2	6	10.00%
21–30	9	14	23	38.33%
31–40	10	5	15	25.00%
41–50	6	5	11	18.33%
51–60	3	1	4	6.67%
61–70	0	1	1	1.67%
Total	32	28	60	100.00%

composed of 25 real patterns in the training set and 25 fake patterns generated by the model. The interviewees were asked to classify each pattern without knowing the proportion of two kinds of patterns. The comparison between a part of these two kinds of patterns is shown in table 6. The experimental results show that the accuracy of interviewees' judgment is concentrated between 40% and 60%, and the number

Table 6

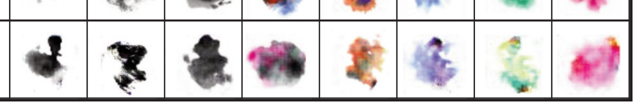
COMPARISON OF REAL PATTERNS AND FAKE PATTERNS	
Real patterns	
Fake patterns	

Table 7

MANUAL EVALUATION OF EXPERIMENTAL RESULTS		
Accuracy	**People in this range**	**Proportion in this range**
100%–80%	1	1.67%
80%–60%	3	5.00%
60%–40%	52	86.67%
40%–20%	4	6.67%
20%–0%	0	0.00%

of interviewees in this area accounts for 86.67%, as shown in table 7. Moreover, most of the interviewees showed more uncertainty and conjecture during the test. This means that most of the respondents, including the design-related practitioners, cannot distinguish the authenticity of the resulting pattern. That is to say, the tachisme apparel pattern generated by the method in this study has a high degree of authenticity, and the model discriminator's ability to judge the research target is close to human through learning. To validate the effectiveness of tachisme apparel patterns designed by the method proposed in this study, we use some patterns generated by the model to design apparel products, as shown in table 8. The design results show that the regional characteristic pattern designed by the method in this study can be well applied to apparel products. And to a certain extent, it presents the aesthetic features and cultural semantics of Chinese tachisme techniques.

Table 8

PRODUCT DESIGN EFFECTS USING MACHINE-DESIGNED PATTERNS				
Machine-designed patterns				
Product design				

CONCLUSION

This study builds and optimizes the digital design model of regional characteristics apparel pattern driven by GAN. In comparison with conventional apparel pattern design ways, this method has the advantages of high automation, productivity, flexibility and resource conservation; compared with other types of generation model and the mainstream GAN model, it is more suitable to deal with regional characteristics of apparel patterns. The specific performance is to solve the training difficulties such as fewer samples, and miscellaneous specifications, and show better performance in the training process, generated results and pattern diversity. This study provides a new solution to the problem that the high development demand of regional characteristic apparel pattern does not match the old creation method. This study will contribute to the digital preservation of regional apparel civilization, the innovation and upgrading of apparel industry design and the promotion of marginal benefits of apparel design.

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Authors:

HAN CHEN[1], LEI SHEN[1], XIYING ZHANG[1], XIANGFANG REN[1], MINGMING WANG[2], XUE MIN[1], XUE LI[1]

[1]Jiangnan University, Faculty of Design, Department of Apparel,
1800 Lihu Dadao, Binhu District, 214122, Wuxi, China
e-mail: chenhanisaac@163.com, 250915195@qq.com, jack-ren@stu.jiangnan.edu.cn,
602653921@qq.com, 747473754@qq.com

[2]Fudan University, Faculty of Computer Science and Technology, Department of Machine Learning,
825 Zhangheng Road, 201203, Shanghai, China
e-mail: 443910752@qq.com

Corresponding author:

LEI SHEN
e-mail: 71952573@qq.com