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## Research on Computer Vision-Assisted Ethnic Pattern Design Teaching and Cultural Identity

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**Abstract** The arrival of the digital era has brought new opportunities for the protection and inheritance of traditional culture. Ethnic patterns, as an important carrier of cultural heritage, carry deep historical heritage and national spirit. This study constructs an intelligent generation system of ethnic patterns based on CA-GAN model and applies it to the teaching of ethnic pattern design courses to enhance the cultural inheritance effect and national identity. The methodology adopts generative adversarial network technology, extracts the content features and style attributes of patterns through content encoder and attribute encoder respectively, and realizes high-quality ethnic pattern generation by combining the attention mechanism. The study uses a database containing 6438 ethnic patterns for model training, and sets the number of training rounds to 10000 epochs and the batch size to 128. The experimental results show that the CA-GAN model performs well in objective evaluation indexes, with the PSNR value reaching 33.15, the SSIM value reaching 0.927, and the FID value decreasing to 10.44, which is an improvement from 10.65% to 19.93% compared with the comparison methods, respectively. 10.65% to 19.93%, 4.51% to 15.59% and reduced 22.38% to 38.77% respectively compared to the comparison method. The subjective evaluation showed that the composite score of the generated pattern reached 4.63. The results of the cultural heritage and national identity survey showed that students and teachers recognized the generative schema, and the emotional resonance dimension of the national identity survey was rated at 4.63 points. The study shows that the introduction of computer vision technology effectively improves the teaching effect of ethnic pattern design courses and provides a new path for the digital inheritance of traditional culture.

**Index Terms** Computer vision technology, ethnic pattern design, CA-GAN model, cultural heritage, national identity, generative adversarial network

### 1. Introduction

The course of ethnic pattern design is a core course in visual communication design [1]-[3]. Its main function is to enable students to understand the ethnic costume culture and lay a foundation for the inheritance of ethnic culture and skills. Ethnic patterns have a wide range of themes, rich connotations and diverse forms, and are widely used in contemporary visual communication design [4]. Ethnic patterns are usually auspicious patterns. They express people's wishes and ideals through the meanings, homophones or additional words of certain natural objects, and are mainly popular among the folk [5], [6]. For thousands of years, in the process of the transmission and development of ethnic patterns, a rich pattern system has been formed, becoming a concentrated representative of ancient Chinese traditional culture [7].

However, in today's globalized fashion arena, ethnic pattern design courses are not only about design, but also an important carrier to enhance cultural heritage and national identity [8], [9]. National culture is the sum of unique values, beliefs, customs, art forms, etc. formed by a nation in the process of long-term historical development [10], [11]. It reflects a nation's way of life, aesthetic interests and wisdom crystallization [12]. And national identity refers to an individual's sense of identification with the nation to which he or she belongs, including identification with the history, culture, language, religion and other aspects of the nation [13], [14]. In the course of ethnic pattern design, the application of cultural inheritance and national identity can enhance the cultural connotation and artistic value of visual communication design works, making it more personalized and charming, and how to enhance the heritage of national culture and national identity in ethnic pattern design courses has become an important issue facing vocational schools [15]-[18].

This study proposes an innovative program to introduce computer vision technology into the teaching of ethnic pattern design courses. First, an intelligent ethnic pattern generation system based on CA-GAN model is constructed to realize high-quality and diversified ethnic pattern generation by improving the structure of traditional generative adversarial network and introducing the attention mechanism and multiple loss function constraints;

second, a teaching mode of ethnic pattern design course integrating computer vision technology is designed, and the intelligent generation system is used as an auxiliary tool for teaching, and human-computer interaction is used to Enhance students' learning experience and cultural cognition; finally, verify the program's role in enhancing the effect of cultural inheritance and strengthening the sense of national identity through empirical research, so as to provide theoretical basis and practical guidance for the digital transformation of visual communication design education.

## II. A study of the ethnic pattern design curriculum with the intervention of computer visualization techniques

### II. A. Generative Adversarial Network Modeling Based on Computer Vision Techniques

#### II. A. 1) Modeling framework

The core of Generative Adversarial Networks [19], [20] lies in the generator  $G$  as well as the discriminator  $D$ . The generator is a neural network that can perform image generation, where the input can be a certain image or some random data. After feeding this data into the generator, the generator produces a target image output. The discriminator is intuitively a very simple neural network that takes an image input and outputs a probability value that makes a prediction about its truth or falsity.

The mechanism for generating an adversarial network can be roughly described as follows: first some data plus some random noise is taken as input to  $G$ , and  $G$  generates a fake image based on this input. Then these target pictures and some real pictures are used as inputs to  $D$ , so that  $D$  can make a judgment on the authenticity of these pictures. When  $D$  makes a judgment, then according to the results of  $D$  judgment through the calculation of the loss function after the backpropagation, the parameters of  $G$  and  $D$  are tuned to improve the ability of  $D$  to discriminate between true and false pictures.

#### II. A. 2) Formula analysis

The design of the objective function of the generative adversarial network is the key to its ability to achieve success, and the following will illustrate the training process of the generative adversarial network by analyzing the objective function of the generative adversarial network:

$$\min_G \max_D V(D, G) = E_{x \sim P_{data}(x)} [\log D(x)] + E_{z \sim P_z(z)} [\log(1 - D(G(z)))] \quad (1)$$

where  $G$  and  $D$  represent the generator and discriminator respectively, while  $P_{data}$  represents the real image dataset and  $P_z$  represents the input of  $G$ . From the objective function, it can be seen that this is a max-min optimization problem, and breaking it down a bit reveals that it actually corresponds to the optimization process of  $G$  and  $D$ , therefore, breaking down the objective function can yield the objective function when optimizing the two different parts:

$$\min_G V(D, G) = E_{z \sim P_z(z)} [\log(1 - D(G(z)))] \quad (2)$$

$$\max_D V(D, G) = E_{x \sim P_{data}(x)} [\log D(x)] + E_{z \sim P_z(z)} [\log(1 - D(G(z)))] \quad (3)$$

From the disassembly of the objective function, it can also be seen that the training of  $G$  and  $D$  is not synchronized, and when optimizing  $D$ , only the output of the image generated by  $G$  is actually used, which is not related to  $G$  itself, whereas when optimizing  $G$ ,  $G$  and  $D$  are treated as a whole, and  $D$  is utilized to judge the merits of the generated image. Therefore, an iteration of training a generative adversarial network can be viewed as first training  $D$  and then training  $G$ .

### II. B. Ethnic pattern generation based on CA-GAN modeling

#### II. B. 1) CA-GAN model structure

This study utilizes a derivative of GAN, i.e., CA-GAN model, to achieve mapping between different attributes of learned ethnic patterns.

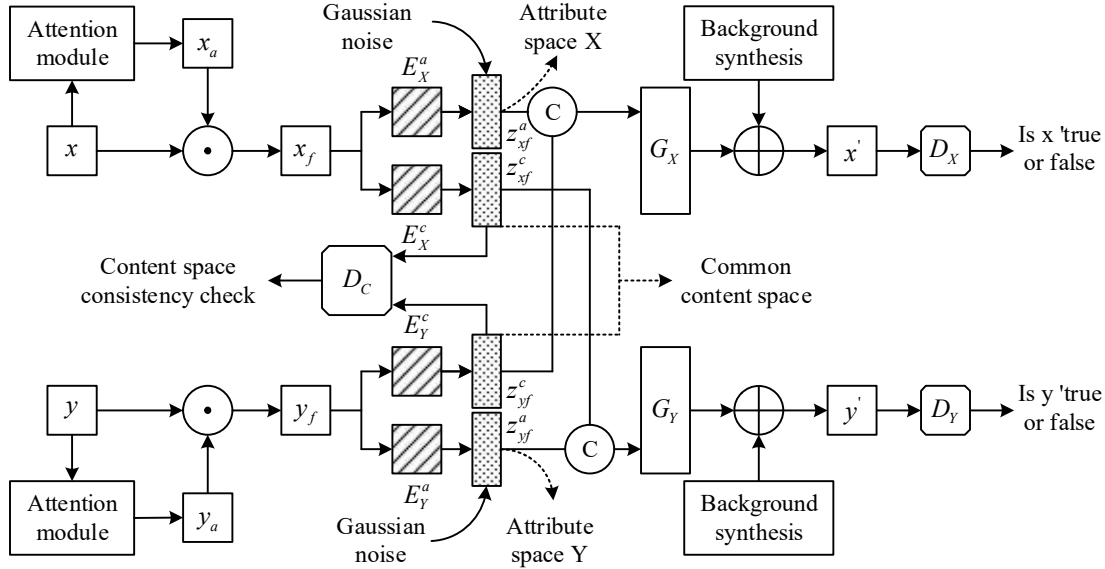
The study proposes the CA-GAN model, which encodes an image into 2 latent vectors, representing the content and attributes of the image, respectively, which are then fused to generate the final image. Also, CA-GAN introduces an attention mechanism [21], which allows the model to focus on the common content in ethnic patterns. The network architecture and key modules of the CA-GAN model proposed in the study are shown in Fig. 1, where Fig. 1(a) is the general architecture, which demonstrates the foreground highlighting process of the attention module as well as the process in which two images with different attribute domains are mapped by exchanging their latent features and mapping them to the attribute space and content space, respectively. Fig. 1(b) shows the creation process of the attention map and Fig. 1(c) shows the synthesis process of the background image. The following is

the specific algorithmic process of the CA-GAN model, which is realized as follows with the transformation of the image from the X domain to the Y domain:

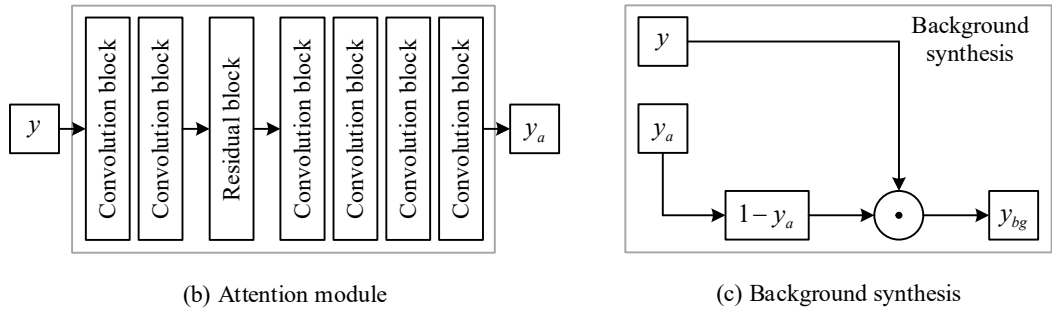
**Step 1: Extraction and exchange of content and attribute features**

First, the sample  $x$  is sent to the attention module to generate the corresponding attention graph  $x_a$ , i.e.,  $x_a = A_X(x)$ . Next,  $x$  and  $x_a$  are fused to obtain the augmented foregrounded graph  $x_f$ , which is fused as follows:

$$x_f = x \square x_a \tag{4}$$



(a) CA-GAN backbone structure



(b) Attention module

(c) Background synthesis

Figure 1: Overall structure Diagram of CA-GAN

Then  $x_f$  is fed to the attribute encoder  $E_X^a$  and the content encoder  $E_X^c$  in the image domain  $X$  to produce the attribute encoding  $z_{x_f}^a$  and the content encoding  $z_{x_f}^c$ , respectively. At the same time, similarity processing is performed on the sample  $y$  in the image domain  $Y$  to obtain  $z_{y_f}^c$  and  $z_{y_f}^a$ . CA-GAN will exchange and fuse the above latent vectors to merge  $z_{x_f}^a$  and  $z_{y_f}^c$  by simple vector splicing approach. The spliced vectors will be sent to the generator  $G_X$  to produce an image  $x'_f$  in the  $X$  domain. The image generated by the attention module contains only foreground objects, in order to obtain a complete image, it is necessary to blend the background elements by background synthesis, which is done as:

$$x' = y_a \square x'_f + (1 - y_a) \square x \tag{5}$$

$$y' = x_a \square y'_f + (1 - x_a) \square y \tag{6}$$

This gives the image obtained by the first exchange of content and attribute features, and also completes the conversion of the image from the  $X$  domain (white painting) to the  $Y$  domain (brush painting).

**Step 2: Cross-loop consistent verification of generated images**

Cross-loop consistency constraints need to be imposed on the CA-GAN model during training to ensure the correctness of the mutual mapping between the images in the  $X$  and  $Y$  domains. In Step 1,  $x$  and  $y$  are encoded into the common content space and unique attribute space, respectively, and their content space and attribute space are also exchanged and decoded to generate the exchanged images  $x'$  and  $y'$ . However, in step 2,  $x'$  and  $y'$  are treated as inputs and processed in the same way as in step 1, i.e., decoupled by the encoder to extract the latent vectors in the attribute space and the content space, and a similar swapping process is again performed (as described in step 1) to obtain the images in the  $X$ -domain and the  $Y$ -domain, respectively, written as  $x''$  and  $y''$ .

According to the theory of cross-cycle consistency, the reconstructed images  $x''$  and  $y''$  should be the same as the original images after the 2nd exchange of coding space (i.e.,  $x''$  and  $y''$ ). The loss function  $L_{cc}$  is used in training to bound this result.

In this paper, Gaussian noise is introduced as a special type of multi-style vector during training. Specifically, the CA-GAN model will generate Gaussian-distributed random noise  $z$  in the latent space during the training process, which will be fed to the generator as an attribute representation of the image. The decoder will then reconstruct the random noise  $z$ , which means that if the image is generated from random noise as its attribute vector, the CA-GAN model requires that after the image is mapped back to the input noise by the attribute encoder in the  $Y$ -domain, it remains equal to the original input noise.

## II. B. 2) Loss function

In order to ensure the stability of model training, this paper uses several loss functions to constrain the training process of CA-GAN.

### (1) Adversarial loss

Adversarial loss includes content adversarial loss and attribute adversarial loss. For content adversarial loss, the main content elements in different styles of ethnic patterns can be encoded into a common latent space. Therefore, in this paper, the discriminator  $D_c$  is utilized to distinguish the content encoding of 2 images in different domains so that they are mapped to the same content space. For the content encoder and content discriminator, the content adversarial loss is denoted as:

$$L_{ac} = E_x \left[ \frac{1}{2} \log D^c(E_X^c(x)) + \frac{1}{2} \log(1 - D^c(E_X^c(x))) \right] + E_y \left[ \frac{1}{2} \log D^c(E_Y^c(y)) + \frac{1}{2} \log(1 - D^c(E_Y^c(y))) \right] \quad (7)$$

The domain discriminators  $D_X$  and  $D_Y$  are used to discriminate whether the images generated by  $G_X$  and  $G_Y$  belong to their target domain or not, using the regular discriminator loss  $L_{ad}$ . Here, CA-GAN specifically uses the least squares loss to reduce the instability in training.

### (2) Cross-loop consistent loss

For the cross-loop consistent loss, the images  $x'$  and  $y'$  are generated by exchanging their attribute and content representations, since the CA-GAN model decouples the representation of the images in a shared content space and a unique attribute space. Again,  $x'$  and  $y'$  are fed into the encoder in order to encode their contents and attributes separately and exchanged in order to generate new corresponding image pairs  $x''$  and  $y''$ . In this paper, we use L1+MS-SSIM to check the cross-cycle consistency of the model as:

$$L_{cc} = E_{x,y} [\|G_X(E_Y^c(y'), E_X^a(x')) - x\|_1 + \|G_Y(E_X^c(x'), E_Y^a(y')) - y\|_1] + F_{ms-ssim}(x, x') \quad (8)$$

Here,  $x'$  and  $y'$  are the images generated after the first exchange of content space and attribute space, respectively. The MS-SSIM function is computed using a multi-scale SSIM function to improve the quality of ethnic pattern generation by paying more attention to the local features of the image:

$$MS-SSIM(x, y) = [l_M(x, y)]^{\alpha_M} \cdot \prod_{j=1}^M [c_j(x, y)]^{\beta_j} [s_j(x, y)]^{\gamma_j} \quad (9)$$

where  $x, y$  denotes the two images in comparison,  $M$  denotes the different scales of the images,  $l, c, s$  denotes the brightness, contrast and structure of the images, respectively, and  $\alpha, \beta, \gamma$  are constants.

### (3) Reconstruction loss

To further ensure that the image content coding and attribute coding decoupled by the encoder can indeed represent this image, this paper needs to use additional constraints to safeguard this process during training. Considering that traditional pixel-level L1 or L2 losses can lead to a lack of diversity in the images generated by the model, CA-GAN uses a reconstruction loss  $L_{rec}$  to constrain the above process and further improve the quality of the generated images, which is based on the Charbonnier loss:

$$L_{rec} = (\hat{x}, x) = \frac{1}{hwc} \sum \sqrt{(\hat{x} - x)^2 + \delta^2} \quad (10)$$

where  $h, w, c$  is the height, width and number of channels of the image, respectively.

Finally, the total CA-GAN loss function:

$$L = L_{ac} + L_{ad} + \lambda_1 L_{cc} + \lambda_2 L_{rec} \quad (11)$$

The  $\lambda_1$  and  $\lambda_2$  in Eq. are hyperparameters to balance the weights of  $L_{cc}$  and  $L_{rec}$ .

## II. C. Experimental Setup for Ethnic Pattern Generation

The study uses generative adversarial networks to construct models and investigate the generation of ethnic patterns, including designing experiments and conducting experiments, recording the results and evaluating them using commonly used evaluation methods. In this paper, the current mainstream image generation networks Conditional Generative Adversarial Networks (C-GAN), Progressive Adversarial Networks (Pro-GAN), Style-Driven Generative Adversarial Networks (Style-GAN), and Self-Attention Generative Adversarial Networks (SA-GAN) are used for comparison.

### II. C. 1) Data pre-processing

This experiment uses an image database containing several ethnic patterns. Since the pixels of the images in the given source database are of different sizes, it is necessary to preprocess the data first in order to be able to carry out the experiments on image generation. The specific steps of preprocessing are as follows:

(1) Crop the source image. In the images of the original database, some of the images have different lengths and widths, and all the images are cropped to the same format of length and width.

(2) Filtering of cropped images. After the previous step, some of the original length and width of the image is very different, will be cropped into the visual appearance and other cropped images gap is relatively large, this image will interfere with the training of the model, so in this step to remove these images.

(3) Resampling the filtered images. After the first two steps, the images obtained are the same in length and width, but the pixels are still different, and here the double-cubic interpolation algorithm is used to resample all the images. After preprocessing the data, an image database containing a total of 6438 ethnic patterns is obtained.

### II. C. 2) Evaluation indicators

The subjective evaluation of the generated pattern is to evaluate the image visually, with more uncertainties, and requires a sufficient number of evaluators to get a more reliable result. While the objective evaluation calculates the numerical value through the formula, and compares the goodness of the image through the numerical value. The commonly used evaluation indexes are as follows:

(1) Peak signal-to-noise ratio (PSNR)

Given the original image  $I$  and the reconstructed image  $I'$ , both of which have a resolution of  $M * N$ , its PSNR can be defined:

$$PSNR = 10 * \log_{10} \left( \frac{MAX^2}{MSE} \right) \quad (12)$$

In the above equation  $MAX$  denotes the maximum possible pixel gray value of the image. The larger the PSNR indicates that the image is generated better. The  $MSE$  is the Mean Square Error between the images with the formula:

$$MSE = \frac{1}{M * N} \sum_{i=1}^N \sum_{j=1}^M (I_{ij} - I'_{ij})^2 \quad (13)$$

(2) Structural Similarity (SSIM)

SSIM takes into account the brightness, contrast, and structure of the image and reflects the overall structural similarity of the image. SSIM formula is as:

$$SSIM(x, y) = l(x, y) * c(x, y) * s(x, y) \quad (14)$$

$$l(x, y) = \frac{2\mu_x\mu_y + c_1}{\mu_x^2 + \mu_y^2 + c_1} \quad (15)$$

$$c(x, y) = \frac{2\sigma_{xy} + c_2}{\sigma_x^2 + \sigma_y^2 + c_2} \quad (16)$$

$$s(x, y) = \frac{\sigma_{xy} + c_3}{\sigma_x\sigma_y + c_3} \quad (17)$$

where  $\mu$  denotes the pixel mean of the image,  $\sigma_x$  and  $\sigma_y$  denote the standard deviation of the pixels of the image,  $\sigma_{xy}$  denotes the covariance between the images, and  $c_1, c_2$  and  $c_3$  are all constants.  $l(x, y)$  measures the difference in luminance between images,  $c(x, y)$  measures the difference in contrast between images, and  $s(x, y)$  measures the difference in structure between images. The larger SSIM indicates that the image is generated better.

### (3) FID

FID measures the difference in distribution between the real image and the generated image and is defined:

$$FID = \|\mu_r - \mu_g\|^2 + Tr(\sum r + \sum g - 2(\sum r \sum g)^{1/2}) \quad (18)$$

where  $\mu$  and  $\Sigma$  are the feature vector and covariance matrix of the output of the image collection, respectively,  $r$  is the real image dataset,  $g$  is the generated image dataset, and  $Tr$  is the trace of the matrix. The lower the FID is, the closer the distribution of the generated image to the real image is, and the higher the quality of the generated image is.

### II. C. 3) Experimental environment

The hardware parameters of the experimental environment for this experiment are as follows:

CPU: Intel(R) Xeon(R) CPU @2.30GHz

GPU: NVIDIA Tesla P100

Memory: 32GB

The running software environment is as follows:

Ubuntu: 18.04 operating system

Python: 3.7

Tensorflow: 1.14 deep learning framework

Pytorch: 1.4 deep learning framework

For the ethnic pattern generation model, 10000 epochs were trained, batch size was 128, and the learning rate of both generator and discriminator was 0.0001.

### II. D. Ethnic Pattern Design Courses Incorporating Computer Vision Technology

After confirming that the model in this paper has a good effect on the generation of ethnic patterns, the model is applied to the ethnic pattern design course in a university. In the application practice of ethnic pattern design course of this study, the author investigates the existing conditions of a university, and changes the original ethnic pattern teaching materials on the basis of the course objectives, so that students can learn the content of the teaching materials and feel the effect of the application of computer visualization technology in ethnic pattern design course in the limited classroom learning time.

Taking the combination of multimedia and teacher-guided approach to the narrative, in the creation mode, mainly through the CA-GAN model designed in this paper for ethnic pattern design. In the course design, the teacher first analyzes the design details in different ethnic patterns in detail, and then carries out the design demonstration of ethnic patterns through the model of this paper, and then the teacher leads the students to appreciate the patterns. After students understand the symbolism of ethnic patterns, they can practice the design of ethnic patterns independently, so as to achieve a gradual progression in knowledge content and a gradual enrichment of design details.

### III. Application analysis of ethnic pattern generation model based on computer vision technology

#### III. A. Computational efficiency and hardware cost analysis

In order to evaluate the computational efficiency and hardware cost of the methods in this paper, the training time, inference time, and memory usage of different methods, i.e., Conditional Generative Adversarial Networks (C-GAN), Progressive Adversarial Networks (Pro-GAN), Style-Driven Generative Adversarial Networks (Style-GAN), and Self-Attention Generative Adversarial Networks (SA-GAN), in the same hardware environment are recorded. The computational efficiency and hardware cost of different ethnic pattern generation methods are shown in Table 1. Since, the training time is affected by hyperparameters and training data and is not completely fixed, it is only used as a reference.

The data in the table shows that the training time, inference time, and video memory occupation of this paper's model are, respectively, 4.32h, 0.008s, and 1.81GB, which outperform the C-GAN, Pro-GAN, Style-GAN, and SA-GAN models in all three aspects, indicating that this paper's model outperforms the comparison models in terms of both computational efficiency and hardware cost. The training speed and inference speed are faster than the comparison methods by more than 1.04h and 0.009s, respectively, and the video memory occupation is reduced by 1.57~1.94GB compared with the comparison methods. In summary, the CA-GAN model adopted in this paper meets the requirements of practical applications in terms of computational efficiency and hardware cost.

Table 1: Computational efficiency and hardware cost results

Model	Training time (h)	Inference time (s)	Significant occupancy (GB)
Ours	4.32	0.008	1.81
C-GAN	5.59	0.017	3.62
Pro-GAN	5.73	0.025	3.75
Stytle-GAN	5.36	0.042	3.64
SA-GAN	6.45	0.061	3.38

#### III. B. Evaluation of the effect of ethnic pattern generation

The results of the ethnic pattern generation experiments include two parts, which are the objective quantitative experiment and the subjective assessment experiment. These two experiments comprehensively assess the effect of ethnic pattern generation based on computer vision technology from both objective image quality and subjective image aesthetics.

##### III. B. 1) Objective assessment

This subsection objectively evaluates the generation effectiveness of the CA-GAN ethnic pattern generation model constructed above, using PSNR, SSIM, and FID values as evaluation metrics, and compares it with the Conditional Generative Adversarial Network (C-GAN), Progressive Adversarial Network (Pro-GAN), Style-Driven Generative Adversarial Network (Style-GAN), and Self-Attention Generative Adversarial Network (SA-GAN) for comparison experiments. The results of the objective evaluation of the quality of ethnic pattern generation are obtained as shown in Fig. 2.

Observing the PSNR value and SSIM value, it can be seen that the measured values of the model built in this paper are 33.15 and 0.927, which are 10.65%~19.93% and 4.51%~15.59% higher than the comparison methods, indicating that the model in this paper can better preserve the composition and style of the ethnic patterns and have higher visual similarity. In addition, the output FID value of this paper's model is 10.44, and the output value of the comparison method is between 13.45 and 17.05, which is reduced by 22.38%~38.77% compared with the comparison model, indicating that the ethnic patterns generated by this paper's method are closer to the training set, and the quality of the patterns is improved. Comprehensive comparison, the ethnic pattern generation effect of this paper's model shows higher consistency in color, texture, pattern layout and overall visual effect, which is the best.

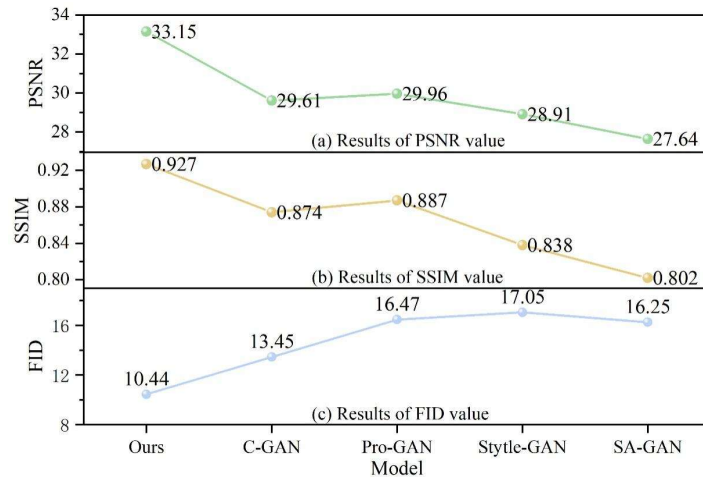


Figure 2: Objective evaluation results of national pattern generation

### III. B. 2) Subjective evaluation

Using the method of random sampling, 10 ethnic patterns were randomly selected from the experimental results to generate samples for subjective evaluation of the experimental results, which were recorded as P1~P10 in turn. Ten experts and scholars in the field of ethnic pattern culture were invited to evaluate the selected 10 ethnic patterns. The five-point quantitative evaluation method was used to divide the three dimensions of the consistency between the ethnic pattern generation scheme and the demand description, the geometric quality and the texture quality of the generated ethnic patterns into five grades, namely, "very consistent/very good", "very consistent/very good", "average", "not very consistent/not very good" and "inconsistent/not good", and the five grades corresponded to 5-1 points from high to low. According to the evaluation scale provided, 10 experts and scholars evaluated the selected 10 ethnic pattern design schemes. The highest score and the lowest score are removed from the results of the expert evaluation of each design scheme, and the average score is taken as the final score of the scheme. According to the results, the pattern generation effect of the national pattern intelligent generation model based on computer vision technology was evaluated, and the survey results of the evaluation index of ethnic pattern intelligent generation were obtained as shown in Table 2.

As can be seen from the table, the 10 selected ethnic motifs have individual and composite scores of 4 or more. Among them, there are 2 ethnic patterns with a composite score of 4.5-5, i.e. P6 and P10. The composite scores of the remaining eight ethnic patterns are all between 4 and 4.5. This indicates that the ethnic patterns generated by the model in this paper are more effective and can be further applied to the teaching of ethnic pattern design courses.

Table 2: The results of the evaluation of national pattern intelligence

National pattern	Consistency	Geometric quality	Texture quality	Comprehensive score
P1	4.53	4.16	4.49	4.39
P2	4.26	4.67	4.49	4.47
P3	4.62	4.55	4.26	4.48
P4	4.17	4.15	4.48	4.27
P5	4.37	4.52	4.51	4.47
P6	4.55	4.76	4.45	4.59
P7	4.69	4.31	4.16	4.39
P8	4.45	4.11	4.22	4.26
P9	4.32	4.57	4.47	4.45
P10	4.72	4.58	4.61	4.64

### III. C. Survey on Cultural Heritage and National Identity

In order to verify the generation effect of the ethnic pattern image generation model, this paper uses different sketch images for the generation of ethnic style patterns and evaluates the superiority of the generation scheme through a questionnaire. The questionnaire scoring value is from 1 to 5, and 40 students participating in the ethnic pattern design course as well as 10 professional teachers of the ethnic pattern design course are invited to score the generation scheme. Scores were given in four dimensions, namely, stylistic continuity, visual aesthetics, integrity of

cultural symbols and innovative adaptability, and the larger the mean value, the higher the evaluation of the dimension. The statistical results of the evaluation of the superiority of the cultural heritage of national patterns are shown in Figure 3.

By analyzing the results of the questionnaire, it can be seen that the intelligent generation design scheme of ethnic patterns is affirmed by both students and teachers in the ethnic pattern design course, and the scoring values of ethnic style continuity, visual aesthetics, integrity of cultural symbols, and innovative adaptability of the generated patterns are 4.56, 4.65, 4.60, and 4.72 respectively, and the comprehensive cultural heritage score is 4.63. It indicates that the ethnic pattern generation scheme based on computer vision technology can better continue the stylistic characteristics of ethnic patterns and obtain visual identity.

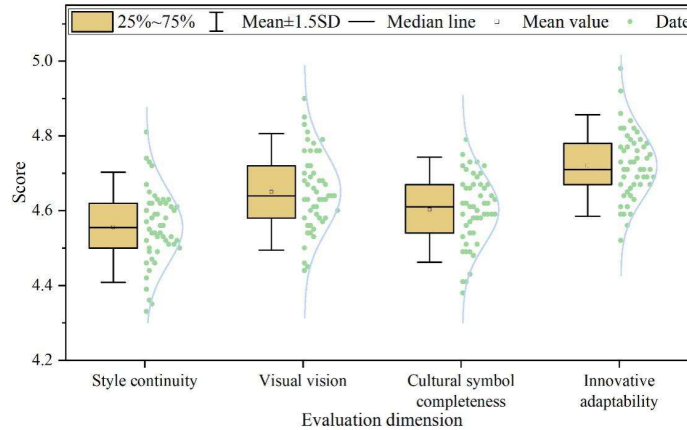


Figure 3: The national design culture passes the excellence assessment statistics

In addition, in order to evaluate the embodiment of the national pattern generated by the scheme of this paper for national identity, a questionnaire survey based on the four dimensions of emotional resonance, cultural cognition, group cohesion, and social identity was also designed. Using the same survey methods and objects as above, the statistical results of the national identity survey are obtained as shown in Figure 4. From the figure, it can be seen that the national pattern generated by the program of this paper has a national identity embodiment rating value of 4.63, 4.49, 4.45, 4.36 in the four dimensions of emotional resonance, cultural cognition, group cohesion, and social identity, respectively. Among them, the dimension of ethnic emotional resonance achieved the highest rating, and the ethnic patterns generated by the scheme of this paper can make students or teachers feel the pride and emotion of national culture for a year, and have a great degree of identification with ethnic patterns.

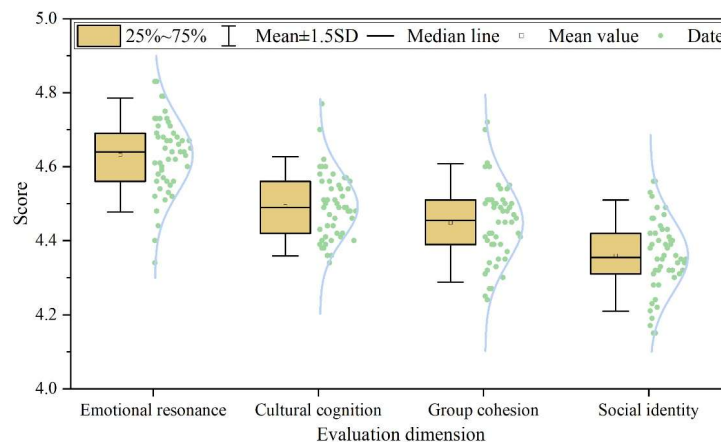


Figure 4: National identity survey statistics

#### IV. Conclusion

This study verifies the significant effect of computer vision technology in cultural inheritance and national identity enhancement by constructing CA-GAN model and applying it to the teaching practice of ethnic pattern design course. The experimental results show that the CA-GAN model reaches 4.32 hours, 0.008 seconds and 1.81 GB in terms

of training time, inference time and video memory occupation, respectively, which is an obvious advantage in computational efficiency compared with traditional methods. The objective evaluation metrics show that the model generates ethnic patterns of excellent quality, with a FID value of 10.44, which is reduced by 22.38% to 38.77% compared with the comparison method, indicating that the generated patterns are closer to the distribution of real ethnic patterns.

The subjective evaluation results further confirmed the effectiveness of the model. 10 experts and scholars evaluated the 10 randomly selected generated patterns, and the comprehensive scores were all above 4, with 2 of them scoring 4.5 or more, indicating that the generated ethnic patterns have gained professional recognition in terms of visual effect and cultural expression. The evaluation of cultural heritage superiority shows that the scores of the generated solutions in the four dimensions of stylistic continuity, visual aesthetics, integrity of cultural symbols and innovative adaptability are 4.56, 4.65, 4.60 and 4.72 respectively, indicating that the computer vision technology is able to effectively maintain the traditional characteristics of ethnic patterns and realize innovative development.

The results of the national identity survey show that the emotional resonance ratings of students and teachers for the generated patterns reached 4.63, which proves that the technology-assisted teaching mode can effectively stimulate learners' national emotions and cultural pride. The introduction of computer vision technology not only improves the teaching efficiency of the ethnic pattern design course, but more importantly, it explores a new path for the digital inheritance of traditional culture, and provides a strong support for the cultivation of students' cultural self-confidence and sense of national identity.

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