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Research on the Application of Computer Visual Technology to Enhance Cultural Inheritance and National Identity in Ethnic Pattern Design Courses

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ABSTRACT

In this paper, first of all, the data preprocessing of ethnic patterns is carried out through image segmentation and grayscaling processing methods, and then the image processing technology is applied to the feature extraction of ethnic dress patterns, and the improved SIFT algorithm is used for the feature extraction of images. The original DCGAN algorithm feature extraction ability is weak generates style picture fuzzy, the effect of the problem of poor, proposed the use of 32-layer deep neural network with residual structure instead of the original 5-layer shallow feature extraction network, significantly enhanced the algorithm's feature extraction ability, enhance the model of the style migration effect. By introducing the objective evaluation index PA of the improved SIFT algorithm, the algorithm was compared with other algorithms, and the segmentation algorithm experiments were carried out with the local patterns of several images, and the results of pixel accuracy PA were obtained to be greater than 0.95, which confirmed that the improved SIFT algorithm was able to realize the accurate extraction of the contours of local patterns. In terms of pattern quality evaluation dimension, the subjective average scores of the amateur group and the expert group are 4.87 and 4.89 respectively, indicating that the ethnic patterns generated by the algorithm of this paper have reached a high standard in quality.

Keywords: ethnic pattern design, image detection, SIFT, feature extraction

1. Introduction

As an important form of ancient human life, national patterns, the earliest cultural phenomenon of mankind, once prevailed among various nationalities in the world and played a great role in the development of primitive society and the progress of mankind itself. Ethnic pattern is the art of drawing form, which expresses the aesthetic interest of the nation and spreads the beautiful character of the nation, which is the innate attribute of ethnic graphics. Once created and formed by the

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forefathers, national patterns will have a strong vitality and will be passed down from generation to generation in accordance with the historical track of the nation, constituting an enduring cultural inheritance relationship in the historical development. The modernization process has the significance of globalization, the cultural personality of the nation is covered by the global mainstream culture, and the individuality is obviously diluted, while the cultural value of the nation is increasingly highlighting its importance, and the call for the promotion of the national culture is rising, and the national identity is becoming more and more prominent [1-2]. Therefore, the cultural traditions and national identity displayed by national patterns are worthy of in-depth study. In addition, with the progress of globalization, the active inheritance and promotion of traditional culture in education not only helps to cultivate students' cultural self-confidence and national identity, but also develops their moral character and aesthetic ability, such as education of ancient poems, education of traditional handicrafts, education of traditional festivals, and education of traditional painting art [3-5]. Whether it is the inheritance of national culture or the perception of national identity, the national pattern design course is undoubtedly a good platform [6].

The research uses computer vision technology for ethnic pattern design, specifically, segmentation, scaling and grayscale processing of ethnic images respectively, then using clustering algorithm and improved SIFT algorithm to extract colors and features of ethnic patterns, and introducing DCGAN algorithm to realize ethnic pattern style migration and generation. On this basis, the method is integrated into the course to realize a new model of ethnic pattern design course. Finally, the feasibility of this paper's method is tested through the validation of the feature extraction of ethnic patterns and the generation effect of ethnic patterns, and its application advantages in enhancing cultural heritage and national identity are further explored through the practice of ethnic pattern design courses.

2. Overview

In education, the integration of non-heritage culture and national culture in order to inherit culture has been seen for a long time. Literature [7] integrates traditional auspicious patterns into art education, which not only realizes the inheritance and dissemination of culture, but also realizes the innovative development of modern art education. Similarly, literature [8] introduces to the integration of traditional symbol elements into modern product design, which not only innovates the traditional symbol cultural inheritance path, but also strengthens the training of design talents. Literature [9] explored the inheritance of traditional cultural elements in the teaching of modern public design courses, showing that the current curriculum education is based on technical inheritance, which stimulates students' interest and also enhances the sense of national identity. Literature [10] believes that the key point in the protection of non-heritage handicrafts is the practical behavior, ability, and environment of inheritance, and it is undoubtedly an excellent condition to carry out inheritance and cultivate the inheritors in education, when at the same time, it is also necessary to combine with social inheritance in order to expand inheritance strength. In addition, literature [11] mentions that the sustainable development of NGT requires local cultural participation, cultural education, cultural identity, cultural value, cultural and tourism integration, and adaptive adjustment and support from government departments. Literature [12] designed a multi-source information integration platform through information fusion technology to integrate the knowledge of intangible cultural heritage and national handicraft culture with art education to jointly complete the inheritance path of intangible handicraft. To a certain extent, education does inherit culture, when there are still some limitations. Taking pattern culture as an example, the display and interpretation of patterns need to use multimedia equipment or more advanced intelligent equipment, but such educational inheritance is never a long-term solution. Need to use modern technology to optimize the display of patterns, as well as the details of the pattern itself to obtain knowledge, so that students can better understand the pattern, heritage culture. Computer vision technology has such magic power, which can acquire, process, analyze, understand and extract valuable information from images and videos [13].

3. Ethnic pattern design course design based on computer vision technology

3.1. Ethnic pattern preprocessing

3.1.1. Ethnic Image Segmentation Algorithm. The edge detection segmentation algorithm of an image is mainly achieved by detecting the edges of different regions of an image by using the feature that the gray levels of the pixels in different regions of an image are not continuous. A localized discontinuity in an image is called an edge of the image, which can be considered as the beginning of an image region or the end of an image region. For the edge position it corresponds to the extreme point of the first order derivative and to the point past zero (zero crossing point) of the second order derivative. Therefore, they can be calculated using differential operators. Currently the commonly used first order differential operators are Roberts operator, Prewitt operator and Sobel operator, and the second order differential operators are Laplace operator and so on.

There are two main methods based on region splitting. One is region growing method and the other is region splitting and merging method. Both of these segmentation methods are serial region techniques and the subsequent processing steps of each method need to be determined based on the results of the previous steps. The basic principle of the region growing segmentation algorithm is to aggregate pixel points with similar characteristics to form regions. The region splitting and merging algorithm, on the other hand, is the opposite of splitting regions with different characteristics to form subregions.

3.1.2. Ethnic image scaling algorithms. Currently there are two main mainstream image scaling algorithms, which are nearest field interpolation and bilinear interpolation. These two image scaling algorithms are described in detail below.

Assume that the pixels of the target image are scaled to 256×256 and the pixels on the target image are all derived from the original image, which is 512×512 pixels in size. In this case the scaling is done by nearest field interpolation algorithm then the pixel points on the target image are calculated as:

$$X_o = X \times (W_s \div W_o) \tag{1}$$

$$Y_o = Y \times (H_s \div H_o) \tag{2}$$

The position of each pixel point of the target image is denoted as (X, Y) in Equation (1), where (W, H) denotes the size of the width and height of the image pixels before and after scaling, respectively. We get the scaling by dividing the width and height of the original image pixels by the width and height of the target image, and then multiplying the value at the position (X, Y) of each pixel to the specific value of the target image at the pixel point of the original image.

Bilinear interpolation differs from nearest field interpolation in that the bilinear interpolation algorithm calculates the value (gray value or RGB value) of a pixel point by finding the four pixel points closest to the corresponding coordinates. If the corresponding coordinates of a pixel are (3-5, 4-5), then the four nearest pixel points are (3, 4), (3, 5), (4, 4), and (4, 5). Then, the distance weights of the corresponding coordinates to each of the four points are calculated by the four nearest points, and the values of the target image pixels are derived by multiplying the calculated distance weights by the specific values of each of the four pixel points. The weighting formula is as follows:

$$X_1 = (X_1 \div X_r) \times (X_r, Y_r) \tag{3}$$

$$X_2 = ((X_r - X_1) \div X_r) \times (X_1, Y_l) \tag{4}$$

$$X = X_1 + X_2 \tag{5}$$

where (X_1, X_2) is the value of the requested coordinate, (X_r, Y_r) is the pixel value of the nearest point to the right of the point, and (X_l, Y_l) is the pixel value corresponding to the left of the point.

3.1.3. Ethnic image grayscale processing. The grayscale processing algorithm of an image is mainly for the processing of the color space of each pixel in the image. In this thesis the RGB color space model is used, and the general image grayscale processing algorithm is to traverse each pixel in the image and then sum the RGB values of each pixel to take the mean. The formula is:

$$Gray = \sum_{i=0}^{n} \left((R_i + G_i + B_i) / 3 \right) / n \tag{6}$$

where n represents the number of pixel points and R_i, G_i, B_i represents the specific value of the RGB color space at i pixel points respectively. In addition to the general grayscale processing technique there is the RGB color space model is subjected to a psychological formula to obtain a grayscale image. The formula is:

$$Gray = \sum_{i=0}^{n} \left(R_i \times 0.299 + G_i \times 0.587 + B_i \times 0.114 \right) / n \tag{7}$$

In Equation (7) the R, G and B values of each pixel point i are multiplied by the corresponding coefficients respectively so that the RGB color of each pixel point is calculated uniformly finally the color image is converted into grayscale image.

3.2. Ethnic pattern feature extraction

3.2.1. Ethnic Color Extraction and Color Matching Relationship Construction:

1) K-means clustering algorithm. The K-means clustering algorithm (K-Means) used for color extraction is an algorithm that performs clustering by constant iteration, which divides the data into K groups, and constantly calculates the sum of squared errors between the groups until the function converges. This algorithm is represented by the function:

Let dataset $X = \{x_i \mid i = 1, 2, \ldots, n\}$ be the data to be clustered, and the objective is to divide dataset X into K groups, $P_k = \{C_i \mid i = 1, 2, \ldots, k\}$ so that the squared error function $f(P_k)$ is minimized, then P_k is the result of clustering the groups. The function $f(P_k)$ is formulated as:

$$E = \sum_{i=1}^{k} \sum_{p \in c_i} | p - m_i |^2 \tag{8}$$

E is the sum of the squared errors of the groups, where c_i is the i nd group and m_i is the average of the i groups, i.e., the center of the group, calculated as:

$$m_i = \frac{1}{n_i} \sum_{p \in c_i} p \tag{9}$$

where n_i is the sum of the reorganized data items. The important basis for determining whether p belongs to m_i is the distance from point p_i to m_i, and this distance is given by the formula:

$$d(x_{il}, m_{jl}) = \sqrt{\sum_{i=1}^{d} (x_{il} - m_{jl})^2} \tag{10}$$

In the formula, x_{il} is the attribute of x_i on l, and $j \in (1, k), d(x_i, m_j)$ denotes the distance from the i th data to the j th clustering center.

This process can be understood as, after obtaining the number of classifications K, the data to be classified will be randomly determined K center points as the initial clustering center, and then calculate the distance from each point to the center point, the points with a small distance from the center point are classified as a group, and every time an object is classified into a clustering, the center point of the clustering will be re-calculated, and the process is carried out continuously until the local squared error and the minimum time will be terminated.

2) Color adjacency matrix. In the construction of the color relationship network, first of all, the color relationship network refers to the matching relationship between various colors and the weight of each color in a visual scheme to show, in the color relationship network, through the circle surrounded by each small color block to indicate all the colors extracted, the size of each color color block to reflect the weight size of the color, the connecting line between the colors to indicate the matching relationship between the colors, the thickness of the connecting line reflects the two colors, the thickness of the connecting line reflects the two colors. The thickness of the connecting lines reflects the frequency of the two colors appearing together.

In a nutshell, the construction of color network is a process of quantifying and visualizing images. Firstly, we need to quantify the color relationship, i.e., to establish the color adjacency matrix, and then use Python language to express the color adjacency matrix in the form of images. Where the color adjacency matrix expression is:

$$C = \begin{bmatrix} w_1 & & & & & \\ l_{2,1} & w_2 & & & & \\ \vdots & \vdots & \cdots & & & \\ l_{j,1} & l_{j,2} & \cdots & w_j & & \\ \vdots & \vdots & & \vdots & \cdots & \\ l_{n,1} & l_{n,2} & \cdots & l_{n,j} & \cdots & w_n \end{bmatrix} \tag{11}$$

$$\sum_{j=1}^{n} w_j = 1 \tag{12}$$

where w_j denotes the weight of the j nd color, and $l_{n,j}$ denotes the proportion of the sum of the number of times the n th color and the j th color appear together.

3.2.2. SIFT based ethnic pattern feature extraction algorithm. Since the scale space $L(x,y,\sigma)$ at different scales can be obtained from the following equation:

$$L(x,y,\sigma) = G(x,y,\sigma) * I(x,y) \tag{13}$$

where $G(x,y,\sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$ is the 2D Gaussian function and $I(x,y)$ is the image expression. The scale space factor σ is the standard deviation of the normal distribution. Then the differential Gaussian DOG operator in the scale space is given by the following equation:

$$D(x,y,\sigma) = (G(x,y,k\sigma) - G(x,y,\sigma)) * I(x,y) = L(x,y,k\sigma) - L(x,y,\sigma) \tag{14}$$

where k is the scale factor between two neighboring scales.

Next the characteristic points of the image are determined, i.e., the local extremes are found. Each pixel is compared with 26 surrounding pixels (8 pixels around the same layer and 9 pixels at each of the corresponding positions in the upper and lower layers). If the DOG value of the detected point is greater or less than this 26 pixel point, the point is an extreme point, i.e., a feature point of the image at this scale.

Since feature points with low contrast are more sensitive to noise and feature points located on edges are difficult to locate accurately, these two types of feature points should be eliminated. The SIFT candidate feature points of the original image are put into set X_0, and the stabilized points selected from them are put into set X.

The method to eliminate feature points with low contrast is to perform a Taylor series expansion of expression (15):

$$D(x) = D + \frac{\partial D^T}{\partial x}\Delta x + \frac{1}{2}\Delta x^T \frac{\partial^2 D^T}{\partial x^2}\Delta x \tag{15}$$

where Δx is the offset of the candidate feature point x. Since x is the extreme point of DOG function, $\frac{\partial}{D}(x)\partial x = 0$, which is solved as $\Delta x = -\frac{\partial^2 D^{-1}}{\partial x^2}\frac{\partial D(x)}{\partial x}$. The exact position and scale of the final candidate point $\hat{x}$ is obtained through several iterations, which is brought into Eq. (16) to obtain $D(\hat{x})$, and then its absolute value $|D(\hat{x})|$, which is the contrast ratio. Set the threshold value of contrast as T_δ, then the rejection formula is:

$$\begin{cases} x \in X \left| D(\hat{x}) \right| \geq T_c, x \in X_0 \\ x \in X \left| D(\hat{x}) \right| < T_c, x \in X_0 \end{cases} \tag{16}$$

Hessian matrix is used in eliminating the feature points on the edges:

$$H = \begin{bmatrix} D_{xx} & D_{xy} \\ D_{xy} & D_{yy} \end{bmatrix} \tag{17}$$

where D_{xx}, D_{xy}, D_{yy} is the pixel difference at the corresponding position in the neighborhood of the candidate point. Assume that the minimum eigenvalue of H is β and the maximum eigenvalue is α. The values of the trace and determinant of H are:

$$Tr(H) = D_{xx} + D_{yy} = \alpha + \beta \tag{18}$$

$$Det(H) = D_{xx}D_{yy} - (D_{xy})^2 = \alpha\beta \tag{19}$$

Let $\gamma = \alpha / \beta$, then the determinant is:

$$\frac{Tr(H)^2}{Det(H)} = \frac{(\alpha+\beta)^2}{\alpha\beta} = \frac{(\gamma\beta+\beta)^2}{\gamma\beta^2} = \frac{(\gamma+1)^2}{\gamma} \tag{20}$$

3.2.3. Improvement of Ethnic Pattern Feature Extraction Algorithm. The RANSAC algorithm when applied to SIFT algorithm can remove some of the matching points with large errors. The key of the RANSAC algorithm is to calculate the coordinate transformation relationship between the feature points of the template image and the corresponding feature points of the image to be matched, i.e., the transformation matrix M [14]. The relationship between the transformation matrix and the feature points is given in the following equation:

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} m_0 & m_1 & m_2 \\ m_3 & m_4 & m_5 \\ m_6 & m_7 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \tag{21}$$

where (x', y') is the coordinates of the feature points on the image to be matched and (x, y) is the coordinates of the feature points on the template image. From the above equation, it can be seen that the transformation matrix M contains 8 degrees of freedom, i.e., 8 unknown parameters are required when calculating it, so each time the solution process needs to utilize 4 sets of matching point pairs.

First assume that the two images contain N pairs of matching point pairs, the basic idea of RANSAC algorithm is as follows:

1) Randomly select $N-4$ pairs from them and substitute them into Eq. (21) to solve the transformation matrix M.

2) Substitute the points $A_i(i=1,2,3,\cdots,N-4)$ in the template image from the remaining 4 pairs into Eq. (22) to obtain the corresponding point MA_i in the image to be matched, and calculate the distance d_i between this value and the point A_i located in the image to be matched on the original match.

$$d_i=(A_i,MA_i)^2 \tag{22}$$

If d_i is less than a pre-set threshold T, the feature point is a correct matching point.

3) Count the number of interior points obtained from step (2) and save these interior points.

4) Randomly select 4 sets of point pairs again among the matched point pairs and jump to step 1). After a number of repetitions, compare the number of inner points obtained at each time, and the transformation matrix corresponding to the maximum value is the transformation relationship between the two images required to be fetched.

By using the final obtained transformation matrix for the matched point pairs obtained by the SIFT algorithm, a part of the outer points can be obtained, which can be removed, thus improving the correct matching rate by a certain amount. However, the matching points obtained by this algorithm may still have wrong matching ones, so the wrong matching points can be further removed by the sorted pairing method proposed in this paper, and the correct matching rate can be further improved.

3.3. DCGAN-based Ethnic Pattern Style Migration and Generation

3.3.1. Convolutional Neural Networks. The convolutional layer extracts image features by moving over the original image. The neurons in the convolutional layer correspond to the local receptive fields in the original image. The convolution kernel is mostly 3×3 in size and performs the convolution operation on the feature maps of the previous layer. The pooling layer, on the other hand, mainly samples the features of the previous layer to reduce the amount of data, and the commonly used pooling operations include maximum pooling, mean pooling, random pooling, and so on.

After inputting the original image X into the CNN, the output of each layer is calculated using equation (23).

$$H_i=f(H_{i-1}\otimes W_i+b_i) \tag{23}$$

where H_i denotes the feature map of layer i, obviously $H_0=X$; W_i denotes the weight of layer i; b_i denotes the offset of layer i; $\otimes$ denotes the convolution operation; $f(\cdot)$ denotes the activation function. The output of the convolution of layer i is summed with the offset b_i of that layer and passed through the activation function $f(\cdot)$ to get the feature map H_i of layer i. Then it is inputted to the pooling layer to downsize the feature map and the feature scale is kept constant. For downsampling, the expression is shown in equation (24).

$$H_i=subsampling(H_{i-1}) \tag{24}$$

After passing through several convolutional and pooling layers, the feature map is next passed into the fully connected network for classification to obtain a probability distribution Y. The expression for the fully connected network is shown in equation (25).

$$Y(i)=P(L=l_i\mid H_0;(W,b)) \tag{25}$$

where l_i indicates the ind category and H_0 is the original input data.

Finally, the difference between the output and the expected value is calculated by the loss function, and the common loss functions are mean square error and negative log-likelihood function. The computed loss is back-propagated by gradient descent method, and the weights W and deviations b of each layer are updated during the propagation process, whose expressions are shown in (26) and (27).

$$W_i = W_i - \eta \frac{\partial E(W,b)}{\partial W_i} \quad (26)$$

$$b_i = b_i - \eta \frac{\partial E(W,b)}{\partial b_i} \quad (27)$$

CNN is suitable for mentioning the training and learning of global features, the model is more adaptable, and currently achieves good performance in areas such as computer vision.

3.3.2. Deep Convolutional Generative Adversarial Networks. CNN is supervised learning, while GAN is unsupervised learning, as mentioned earlier, the training of the original GAN is more difficult, prone to training difficult to converge, gradient dispersion and other problems. Deep Convolutional Generative Adversarial Network (DCGAN) is designed to solve the problems of the original GAN. Although DCGAN does not solve the problem from a theoretical point of view like WGAN, it combines CNN and GAN, and to a large extent, it also reduces the degree of difficulty in training GAN.

3.3.3. Ethnic Pattern Style Migration and Generation. Although DCGAN has made great progress in style migration relative to traditional methods, the generated image styles still have the problems of blurring, abnormal styles and poor overall effect in the overall style migration of clothing. Therefore, this paper makes the following two improvements on the basis of DCGAN:

1) Because the overall style migration constraints are less, it is easy to lead to the generated clothes do not look like a normal dress, i.e., the learned pictures are not like four. To solve this problem, the loss function is optimized in this chapter by using a contrast loss function, which can better learn the relationship between each attribute of the clothes to guide the network to learn a new style.

2) Since DCGAN uses a 5-layer CNN network to extract features, the feature extraction ability of the network is weak and the feature extraction effect is not good enough. Therefore, this chapter strengthens the feature extraction part by using the residual module of ResNet to construct a deep neural network, and at the same time increases the number of network layers to enhance the feature extraction effect to improve the overall style migration effect.

3.4. Incorporate pattern-generating forms of course design

3.4.1. Course content. Ethnic pattern design course is a professional practice course for art and design majors, this course is mainly to cultivate students' observation and creative ability of natural forms through the study and training of traditional patterns, aiming to cultivate students' expressive ability of ethnic pattern redesign, and to strengthen students' imaginative thinking and creativity based on absorbing the art of traditional patterns, combined with sketching and deformation, so as to lay a foundation for the artistic expression of the subsequent professional design This course is designed to cultivate students' ability of national pattern re-design expression. It is also a course to cooperate with the development of cultural industry, promote the creation of cultural works and enrich the spirit of cultural connotation. It is hoped that through the study of this course, students can master the skills of re-designing ethnic patterns, provide professionals for the field of cultural and creative industries, and satisfy the needs of the industry development from the design level.

3.4.2. Teaching of the curriculum. The coursework of Ethnic Pattern Design mainly requires students to use the collected ethnic patterns as design materials to carry out redesign and apply them to products. In the previous course practice, students completed the creation of design works well, and the works were mainly presented in the use of patterns on posters, product packaging, book covers, square scarves, cell phone cases and other products.

4. Ethnic pattern design course practice and analysis

4.1. Ethnic pattern feature extraction effect

4.1.1. Color feature extraction results. In this section, through the extraction of pattern features, sample color extraction is completed, the other samples in the data set are imported into the color extraction algorithm, after the algorithm calculates and the number of primary colors to control, the pattern color scheme extraction results, as shown in Table 1. Pattern color scheme extraction results contain data set sample number, sample display, sample primary color percentage, base color analysis, pattern color analysis, hexadecimal color code and RGB code, the above information can help to improve the accuracy of the subsequent application of the color scheme.

Table 1. Example of the color scheme extraction results

Original image 6 decimal color code RGB code e	Background colour		Pattern color matching	16-forward color code
#140a0(20 10 12)	Black	#140a0c(20 10 12)	Red	#b1382(177 56 45)
			Black red	#7e6e75(117 37 38)
			Brown	#4b3232(75 50 50)
			Olive	#441517(68 21 23)
#5c0f30(92 15 48)	Claret	#5c0f30(92 15 48)	Gray	#7b7b81(23 23 29)
			Gray black	#58515f(88 81 95)
			Red	#8a1b3c(138 27 60)
			Dark blue	#1c142f(28 20 47)
#13113e(19 17 62)	Mazarine	#13113e(19 17 62)	White powder	#dfd9dd(223 217 221)
			Pink	#aa93a1(170 147 161)
			Purple	#6a637d(106 99 125)
			Blue	#393c5f(57 60 95)

The extraction of pattern characteristic color provides color material for national pattern design, promotes the subsequent chapter pattern design and application research, uses typical color matching to enhance the aesthetics of the product, ornamental, so that more Zhuangjin elements into the public's field of vision, and deepen the user's cognition of the national pattern, which contributes to the national culture from the visual dimension.

4.1.2. Tattoo feature extraction results. Through the image smoothing, segmentation, binarization processing to get pattern samples, the other samples in the dataset were imported into the algorithm, after image pre-processing and segmentation, binarization and other extraction of pattern basic morphology, Zhuang brocade pattern feature extraction results as shown in Table 2, which contains the data set sample number, sample display, smoothing processed image, segmented image, binarization results, PA value and other information, for further pattern design to provide basic elements. The table lists the sample pattern pattern feature extraction results and calculates the pixel accuracy PA values of the segmentation results. From the pattern grain feature extraction results, it can be seen that the PA values of all segmentation results of this paper's algorithm for the target pattern are higher than 0.95. This indicates that the algorithm presented in this paper has excellent robustness, is not affected by the image texture, and quickly segments the target pattern, and also predicts the target pixels with a high degree of accuracy to minimize the prediction error. In addition, the algorithm is easy to operate and only requires interactive operations to accomplish the target segmentation task.

Table 2. Extraction results of pattern pattern features

Number	PA value
A03	0.997
B01	0.984
C05	0.961
D05	0.988

4.2. Ethnic pattern generation effects

4.2.1. Experimental environment and experimental data. After the training samples are equalized and sharpened, the style migration experiment is carried out. In this paper, the experimental environment is carried out under windows 10 system, and the experimental environment parameters are configured as shown in Table 3.

Table 3. Table of configuration of experimental environmental parameters

Experimental environment	Parameter configuration
Operating system	Windows10
Development environment	PyCharm
Graphics processor	NVTDIA GeForce RTX40
Programming language	python
Deep learning platform	PyTorch

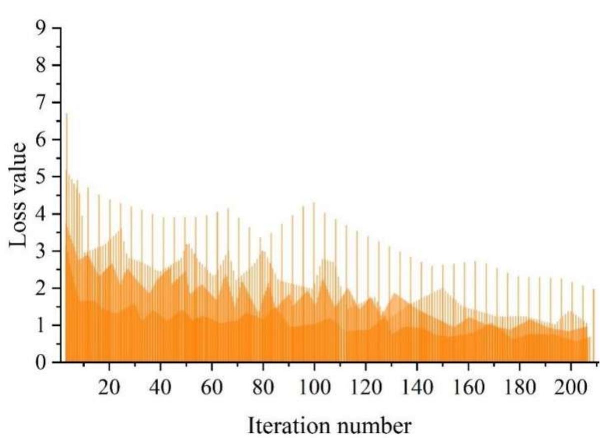
In this study, a total of 2078 as content images of ethnic landscape paintings and 791 ethnic patterns as style images were collected. The distribution of the experimental dataset is shown in Table 4.

Table 4. Distribution of the experimental data

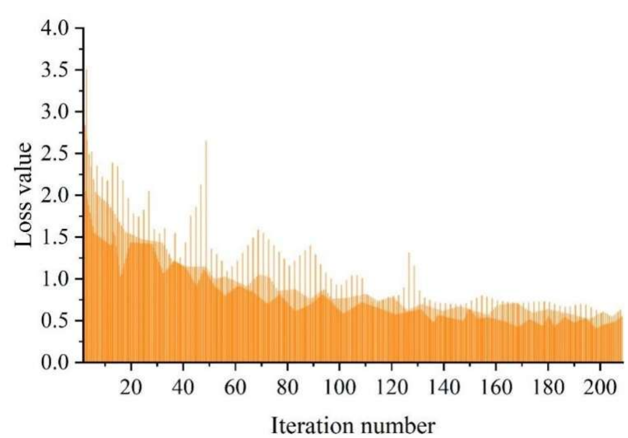
Training sample	Train A	Train B	Train A	Train B	Total
National landscape painting	1761	0	317	0	2078
National pattern	0	691	0	100	791

4.2.2. Training process. Under the same experimental conditions, keep the same training parameters, observe the style migration effect after different iteration times, when the model training cycle iteration 150~200, the model generates image style style stability, with obvious national culture style. When continue to increase the training cycle to increase the number of iterations, the style migration effect will not change greatly, but will bring more computational cost consumption, so the training cycle is set to 200 epoch is more reasonable.

In the improved algorithm model, the cyclic consistency loss function reflects the change of the basic content and structure of the image in the conversion process, and in this experiment, when converting from the ethnic landscape painting to the ethnic pattern, it reflects whether the core content of the ethnic landscape painting, such as the layout of the landscape, and whether the characteristic elements (e.g., mountain peaks, clouds, and water surface) have been well preserved. The cyclic consistency loss function is shown in Fig. 1, and the loss value gradually decreases with the increase of iterations, and the converted image shows the typical ethnic cultural style while retaining the layout and elements of the original painting.



(a)PC1



(b)PC2

Fig. 1. A cyclic consistency loss function

4.2.3. Evaluation of image migration effect. In terms of visual effect, the improved method has better advantages. In order to further make a more accurate evaluation of the generated patterns, the migration effect was evaluated from both subjective and objective aspects. PNSR, SSIM, and FID indexes were used for objective evaluation, and laymen and experts were invited to score and evaluate the subjective evaluation, and the PSNR and SSIM values of different style migration methods are shown in Table 5. Although the quality of the patterns generated by the algorithm in this paper is the best from a visual point of view, the PSNR value and SSIM value of the four transfer algorithms are not much different, so the FID scores of the generated ethnic element patterns and the real ethnic element patterns are also counted, as shown in Figure 2.

Table 5. The PSNR and SSIM values of different style migration methods

Algorithm	PSNR	SSIM
This algorithm	16.01	0.7358
Lap Style	14.27	0.728
Fast Neural Style	18.55	0.6571
VGG19 Style Transfer	17.29	0.7718

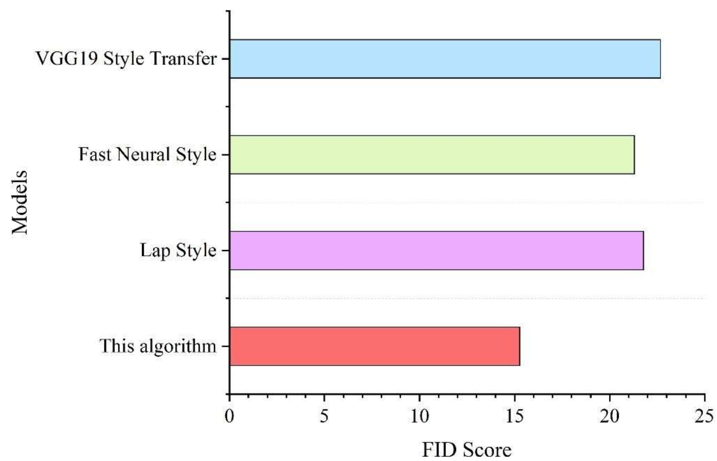


Fig. 2. FID scores of different style migration methods

Although PSNR and SSIM are commonly used image quality evaluation metrics, they do not fully reflect human perception of image quality. Therefore, it is also necessary to combine subjective evaluation indexes to comprehensively assess image quality. The subjective evaluation method takes human as the subject, and scores and evaluates the image to be tested through human observation and perception.

In this paper, a total of 100 observers are invited to score the images to be tested, divided into amateur group and expert group, the number of amateur group is 65, and the number of expert group is 35. The scoring results of the images to be tested are summarized. The subjective evaluation scores of the amateur group are shown in Table 6.The average subjective scores of the four groups of images are shown in Figure 3.

Table 6. Statistics of the subjective scores of the amateur group

	5 points	4 points	3 points	2 points	1 point
Group A	41	14	6	0	0
Group B	4	51	6	0	0
Group C	0	0	57	8	0
Group D	0	24	42	0	0

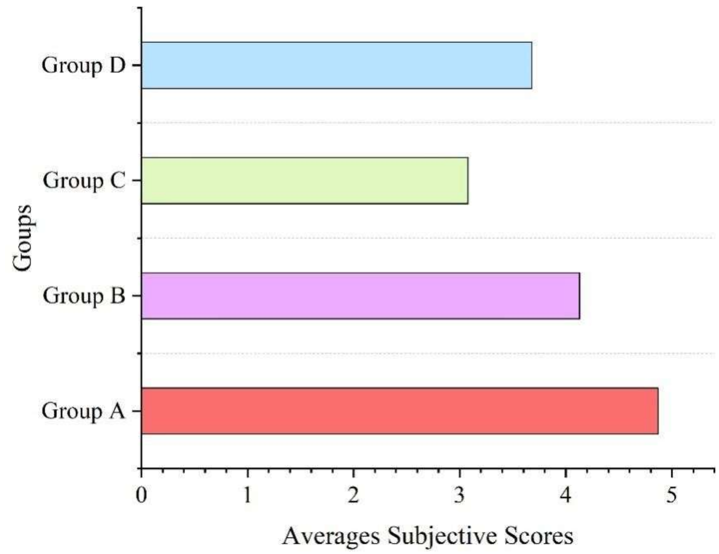


Fig. 3. The average subjective score of the amateur group

The subjective evaluation scores of the panel of experts are shown in Table 7.The average subjective scores of the four groups of images are shown in Figure 4.

Table 7. Statistics of subjective scores

	5 points	4 points	3 points	2 points	1 point
Group A	19	10	6	0	0
Group B	10	22	3	0	0
Group C	0	0	24	6	5
Group D	0	0	30	5	0

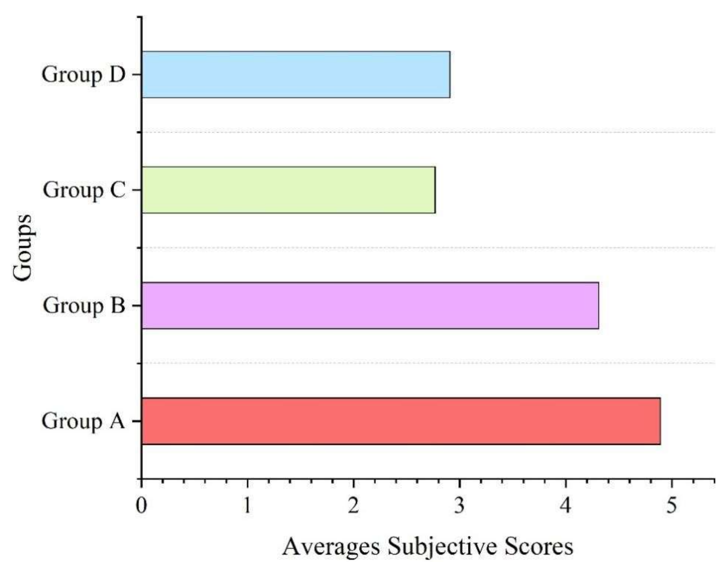


Fig. 4. Average subjective score of the expert group

Groups A, B, C, and D correspond to the improved algorithmic model, LapStyle, VGG19 Style Migration, and Fast Neural Style, respectively.According to the average subjective scores presented in Figs. 3 and 4, it can be seen that in both the amateur group and the expert group, the average subjective scores of the images in Group A ranked the first, with 4.87 and 4.89, respectively.This result indicates that the images based on the This result shows that the improved algorithmic model demonstrates significant advantages in several aspects such as visual effect, content retention, and style integration. This advantage is unanimously recognized by evaluators from different backgrounds, further proving the strength of the algorithm in the style migration task.

4.3. Ethnic pattern design course practice

Pattern design teaching reform oriented to cultural heritage is a practical teaching reform of teaching content, teaching objectives and teaching methods for traditional pattern teaching, which focuses on pattern design, leads students to learn the design practice based on cultural creativity other than the basic knowledge of pattern design teaching, masters the practical skills and innovative creative means of pattern design, and allows students to build up the commercial awareness of design from the basic courses. Awareness. Pattern design practice teaching reform can combine local cultural characteristics through the project teaching mode to continuously launch original cultural products and services, actively develop new pattern art styles, promote the development of characteristic cultural industries, promote the development and production of artistic derivative design and cultural creative products, and accelerate the integration of arts and crafts products, traditional handicrafts with modern technology and elements of the times.

4.3.1. Research tools and subjects. This study was conducted in the form of an online online test, based on the principles of informed consent and autonomy and voluntariness, and the interviewees were students majoring in fine arts and art. IP addresses were limited to one visit, and questionnaire data with a response time of less than 6 minutes were automatically excluded. Questions of the same topic type were presented randomly, and after the questionnaire was completed, the introductory material of the structured text on national identity self-experience was automatically presented, which aimed to arouse the empathy of the subjects and stimulate their motivation for self-analysis. Interested subjects can download the file and fill it out by themselves, and submit it to the researcher after completion. After completing the questionnaire or the structural text, the subjects replied to the name of the main test via WeChat or QQ, and the test fee was available after verification. A total of 341 questionnaire data and 20 text materials were collected in this study.

4.3.2. Descriptive statistical analysis. The mean and standard deviation of the psychological elements of national identity are shown in Table 8. From the table, it can be seen that in the measured group of subjects, all six psychological elements of ethnic identity have high scores and have similar mean and standard deviation, which indicates that in the surveyed group, each element is better constructed into ethnic identity.

Table 8. Means and standard deviations of the psychological elements of ethnic identity

	Average	Standard deviation	N
National identity	6.23	0.9	331
correlation	6.23	0.89	331
importance	5.95	0.9	331
Cultural affinity	6.08	0.92	331
Ideological convergence	6.32	0.83	331
Utility	6.44	0.86	331

4.3.3. Findings and Distinguishing Effectiveness Analysis. The correlation analysis between the total score of the psychological elements of national identity and the content elements is shown in Table 9. The correlation between the dimensions and the total score ranges from 0.6 to 0.9, and it is clear that the correlation of this scale is higher than this range, which signals that the questionnaire does not have a multidimensional structure, but tends to be a whole. For this reason, further exploratory factor analysis will be conducted to see if the questionnaire is unidimensional, i.e., it is exploring whether the 6 elements are integrated into a unified national identity in this group of subjects.

Table 9. Correlation analysis

	National identity	Correlation	Importance	Cultural affinity	Ideological convergence	Utility	Identification factor
National identity		0.931**	0.832**	0.727**	0.863**	0.802**	0.955**
Correlation			0.837**	0.748**	0.857**	0.767**	0.947**
Importance				0.753**	0.742**	0.648**	0.889**
Cultural affinity					0.765**	0.692**	0.862**
Ideological convergence						0.838**	0.922**
Utility							0.864**

P<0.01**

Through spherical identification, a KMO value of 0.972, a spherical identification chi-square value of 16921.174, a degree of freedom of 1841, and a significance of 0.000 were obtained, indicating that there are common factors between the questions, which can be analyzed by factor analysis. Principal component analysis was performed on 60 questions to extract the common factors and perform variance maximization orthogonal rotation.

The factor analysis fragmentation diagram of the National Identity Psychological Elements Scale is shown in Figure 5 (the horizontal axis is the number of components, and the vertical axis is the eigenvalue), and the factor analysis feature extraction of the National Identity Psychological Elements Scale is shown in Table 10. As can be seen from Figure 5 and Table 10, the extraction of feature roots greater than 1 yields six factors, but the variance contribution rate of the first feature factor is as high as 51.34%, which indicates that unidimensionality has strong explanatory power.

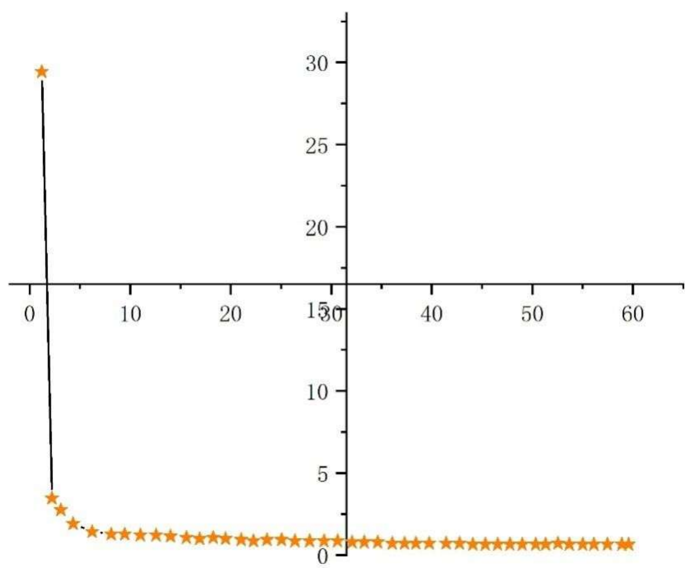


Fig. 5. Gram diagram of factor analysis of psychological factor scale of national identity

Table 10. Feextraction of factor analysis

Element	Start eigenvalue

	Amount	Interpretation of quantity	Accumulate the interpretation amount%
1	30.278	50.46	50.46%
2	3.013	5.02	55.48%
3	2.671	4.45	59.93%
4	1.752	2.92	62.85%
5	1.212	2.02	64.87%
6	1.153	1.92	66.79%
7	0.977	1.63	68.42%

4.3.4. Analysis of forecasting functions. The ethnic identity element scores are shown in Figure 6. The figure shows that there may be a linear relationship between the total identity element score and the ethnic identity element. Therefore a linear regression was performed.

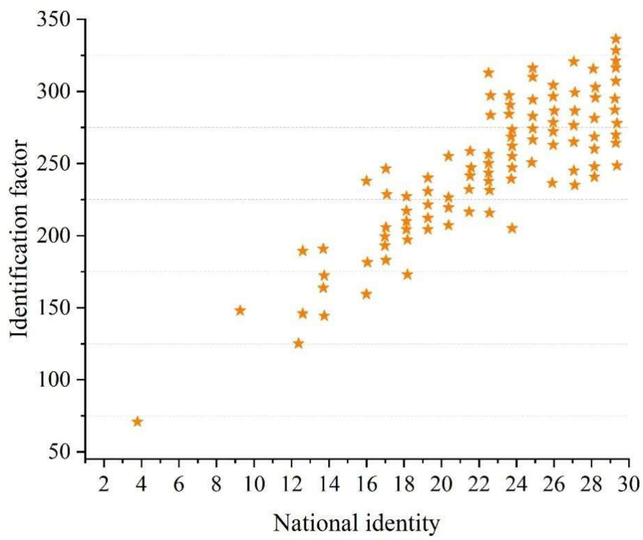


Fig. 6. Scatter plot of ethnic identity elements score

The linear regression results are shown in Table 11, Table 12 and Table 13. R^2 = 0.788, indicating that the fit is good and linearity is established; from the test of variance of the regression equation, the significance p=0.000, indicating that the regression equation is significant; from the test of coefficients, it can be seen that p=0.000, which is significant, therefore, the regression equation is $y = 0.096x + 2.067$. This indicates that the scores of the psychological elements of national identity can effectively predict the scores of the National Identity Scale.

Table 11. Model parameters

Model	R	R^2	Adjust the R square	Standard misestimation
1	0.891	0.795	0.788	2.13572

Table 12. Model variance tests

Model		Quadratic sum	df	The mean square	F	Conspicuousness
1	Regression residuals	5018.071	1	5018.071	1211.792	0.000**1
		1335.442	329	5.176		
	Amount to	6353.513	330			

Table 13. Model coefficient test

Model		Non-standardized coefficients		Standardization coefficient	T	Conspicuousness
1		B	standard error	Beta		
	Constant	2.067	0.771		5.372	0.000**
	Identify the total score of elements	0.096	0.006	0.891	35.729	0.000**

5. Conclusion

The research will improve the SIFT algorithm to extract the color and features of ethnic patterns, then introduce DCGAN algorithm to achieve the ethnic pattern style migration and generation, and finally apply the technique to the pattern design course. The research results show that:

1) the introduction of image segmentation objective evaluation index PA, the algorithm of this paper was compared with other algorithms, and the segmentation algorithm experiments were carried out with the local patterns of several images, and the results of pixel accuracy PA were obtained to be greater than 0.95, which confirms that the algorithm proposed in this paper is able to realize the accurate extraction of the contour of the local patterns.

2) With regard to the pattern quality evaluation dimension, the subjective average scores of the amateur group and the expert group are 4.87 and 4.89 respectively, indicating that the generated ethnic patterns have reached a high standard in terms of quality.

3) Through the data collection of the research subjects, the data of ethnic pattern design course practice were tested and analyzed for reliability and validity, and from the test results, the significance p=0.000, which is significant. It shows that the score of psychological elements of national identity can effectively predict the score of national identity.

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