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Article

Research on Virtual Costume Design for Traditional Cultural Symbols: An Intangible Heritage Display Method Based on Computer Vision Technology

Xiaoxuan Nie * and Li'na Zhao

College of Beauty and Arts, Tongmyong University, Busan, 48520, Korea; ttdxyydda77@sina.com

Abstract: Intangible heritage carries the historical memory and cultural genes of human beings, and the rise of computer vision technology brings new opportunities for its protection and inheritance. In this paper, we start from the application of computer vision technology to the display of intangible heritage, and introduce the convolutional neural network VGG-19 optimization model into virtual clothing design to construct a clothing image style migration model based on traditional cultural symbols. Experiments show that the model's index results in peak sex-to-noise ratio, structural similarity, root-mean-square error and style migration speed are better than the performance of the comparison methods, and its peak sex-to-noise ratio is improved by 5.09%~51.43%, which proves the high quality and high integration effect of the style migration images generated by the model. When using images containing different traditional cultural symbols for apparel image generation, the non-heritage cultural images with better migration effects in terms of texture color, artistic rendering effect, and creativity of the apparel are the celadon style, the New Year's painting style, and the Dunhuang mural style, with the support rate of the respondents being 49%, 35%, and 39%, respectively. The proposed series of methods can assist the design of clothing styles and broaden the application scope of non-heritage traditional cultural symbols.

Keywords: VGG-19; style migration; traditional cultural symbols; virtual clothing design; computer vision technology

1. Introduction

With the development of computer science and the emergence of the metaverse concept, virtual clothing design has become a research hotspot [1-2]. Virtual reality technology, simulation technology, and graphics technology have been applied to virtual clothing design to achieve realistic simulations of fabric simulation and clothing cutting and sewing [3]. Compared to traditional clothing design applications, virtual clothing production technology overcomes spatial and material constraints [4]. It also enables the rapid creation of clothing styles in a virtual environment, showcasing the three-dimensional form of clothing on a mannequin, and reduces fabric waste in physical clothing production through digital technology and precise measurements [5]. Computer vision technology is another core technology in the field of artificial intelligence, having made significant progress in recent years in areas such as intelligent image analysis and three-dimensional reconstruction [6-7]. By integrating computer vision technology into the presentation of intangible cultural heritage symbols, new pathways for the inheritance of intangible cultural heritage have been developed [8].

Currently, virtual modeling technology is being increasingly applied in the field of clothing design. Liu proposed a modeling method based on virtual display in his research on 3D clothing design methods, achieving functions such as virtual modeling of characters, clothing, and accessories. This successfully promoted the transformation of clothing design forms and improved the efficiency of clothing production [9]. Fang et al. introduced computer vision technology to highlight the details of clothing design. They used 3D laser scanning technology to collect laser point data on clothing details and perform 3D reconstruction. This method yields three-dimensional image information entropy greater than two-dimensional images, achieving excellent virtual display effects for fashion design details [10]. Yu, K utilized fashion CAD technology in 2024, employing relevant measurement devices to collect non-contact human body measurement data, completing virtual assembly of fashion samples in CLO 3D software, and using virtual models to showcase the appearance of the sample garments. The fashion samples designed using this method passed fashion pressure tests [11]. In the same year, Yu, Q, and others also utilized digital design tools such as CLO 3D to achieve virtual simulation design of clothing. Unlike Yu, K's research, this study focused on traditional clothing. The results demonstrated that digital tools can rapidly and accurately simulate the production process of traditional clothing, exhibiting high accuracy and practicality [12].

The application of computer vision technology in the display of intangible cultural heritage holds profound significance. Wei et al. explored the creative transformation and innovative development of intangible culture through digital empowerment technologies. The results of the case studies indicated that technologies such as virtual reality and artificial intelligence can effectively protect and inherit intangible cultural heritage [13]. Zhao utilized a three-dimensional convolutional neural network to capture and analyze complex elements of intangible cultural heritage, dynamically showcasing the visual characteristics of intangible cultural heritage and providing interactive digital media technology for cultural dissemination [14]. Huang designed an intelligent architecture based on generative adversarial networks, optimized through training with a large dataset of intangible cultural heritage images, enabling it to accurately extract image features of intangible cultural heritage, achieving an accuracy rate of 97.5% in intangible cultural heritage image capture operations [15].

However, there are few reports on the application of computer vision technology in clothing design. For example, Liu constructed a database of intangible cultural heritage images of ethnic clothing, utilizing a convolutional neural network algorithm and a wireless network-based intangible cultural heritage image recognition model to train ethnic clothing image samples, effectively extracting visual features such as style and color [16]. Kuzmichev noted in his research that artificial intelligence and computer vision technology assist in clothing design, can achieve an accuracy of 95% under stable diffusion conditions and significantly improve the accuracy of textile material drape. Through AI's analytical and generative capabilities, the quality of clothing generation is enhanced [17]. Virtual clothing design technology, when deeply integrated with cutting-edge technologies such as AI, big data, and the Internet of Things, drives continuous innovation and upgrading of traditional cultural clothing design techniques and also plays a promotional role in the dissemination of intangible cultural heritage [18-19].

This paper discusses the characteristics of computer vision technology and its application in the display of non-heritage, and proposes a clothing design method integrating traditional cultural symbols based on the VGG-19 model. First, edge contour extraction and line enhancement are performed on the target content image to avoid color overflow and overlap caused by style migration. Second, the loss function is utilized to extract traditional cultural symbol features and the extracted traditional cultural symbols are used in virtual clothing design. The MS COCO dataset is used as the experimental sample, and the mean square error, peak sex-to-noise ratio, structural similarity, and the speed of style migration are used as the evaluation indexes to train and test the model. The style migration performance of the proposed method and its practical utility in integrating traditional cultural symbols into virtual clothing design are explored through model ablation experiments, comparison experiments and model applicability analysis.

2. Application of Computer Technology in the Presentation of Intangible Heritage

Unique traditional handicrafts, elements of national costumes, folk cultural activities and other non-heritage cultural elements contain rich historical, cultural and artistic values, but in the fast-paced modern society, these precious cultural elements are often marginalized and face serious challenges in protection and inheritance. Computer vision technology can digitally record, analyze and display the contents of non-heritage, so as to revitalize the non-heritage in modern society, and help to solve the many difficulties in the protection and inheritance of non-heritage.

2.1. Efficient Processing of Image Data

Computer vision technology shows remarkable characteristics in terms of efficient processing of image data. The use of image sensors gives the technology the ability to collect image data at high speed and acquire massive image data in a short time. In the intangible cultural heritage protection scenario, it can integrate image data from different channels, such as old photographs collected by the folk, images digitized by museums, etc., which provides a rich and well-organized data base for the comprehensive and in-depth study of intangible cultural heritage, and greatly improves the efficiency of data utilization.

2.2. Feature Extraction and Analysis

Computer vision technology has a powerful feature extraction and analysis capability, which can recognize many types of features from images. In terms of color features, information such as average color and color histogram can be obtained, which helps to accurately analyze NRIs with distinctive color features. For texture features, such as roughness and directionality can also be accurately extracted. Taking the traditional weaving process as an example, texture features of woven fabrics can be accurately captured to distinguish different weaving styles. In terms of shape features, features such as contours and geometric shapes can be extracted very well. For example, for the traditional art of paper-cutting, it is possible to clearly recognize the shape features of paper-cutting works, and then effectively distinguish the differences in the pattern contours of different styles of paper-cutting. With the help of deep learning algorithms, the deep semantic information in the images can also be mined. For images related to ancient cultural heritage, not only can they recognize their external visual features, but also understand the cultural symbolism and other deep content behind them, which can provide strong support for in-depth research of cultural heritage.

2.3. Model Accurate Identification and Classification

Computer vision technology excels in accurate model-based recognition and classification. Pre-trained deep learning models, such as VGG and ResNet in convolutional neural network, can be used for fast recognition and classification of images or videos related to non-legacy. When dealing with ethnic traditional dance videos, these models accurately determine the ethnic affiliation of the dance based on the dancer's movements, costumes, and other features, with remarkable efficiency and accuracy. It is also valuable to build customized models for specific non-heritage protection needs. For example, for the video analysis of endangered traditional handicrafts, the customized model can accurately identify each step of the production process and accurately determine and categorize each link, which is significant in protecting complex and unique traditional handicrafts. Through this precise identification and categorization, both complex traditional building construction techniques and delicate hand embroidery stitches can be accurately recorded and differentiated under computer vision technology.

2.4. Visualization and Interactivity

Computer vision technology can present the processed results in an intuitive visualization way. In terms of traditional dress culture, through computer vision technology, the pattern, color and other elements of the dress can be dynamically displayed, and different styles can be switched to display according to the user's interactive commands, which further enhances the user's understanding of traditional dress culture. Visualization technology can also be used to vividly display its production process, while setting up interactive functions, such as the user can choose to view the detailed operation of a particular step or the comparison between different processes to display, etc., which not only makes the non-legacy culture easier to be understood, but also enhances the public's interest in and attention to non-legacy, thus promoting the protection and inheritance of non-legacy.

3. Virtual Clothing Design Based on Traditional Cultural Symbols

Computer vision technology can digitally collect, analyze and display intangible cultural heritage, and this paper uses it in the virtual clothing design of traditional cultural symbols, and proposes a clothing image style migration method based on the improvement of VGG-19 to realize the virtual clothing design that integrates traditional cultural symbols.

3.1. VGG-19 Model

In the process of image style migration, the application of deep learning methods in image feature extraction has achieved better research results.The VGG-19 neural network model consists of 16 convolutional layers, 5 pooling layers, and 3 fully connected layers, with a convolutional kernel size of 3 × 3, a convolutional step of 1, and a pooling method of maximal pooling maxpool in the pooling layer.Currently, in the deep learning-based image style migration research, the VGG-19 model performs very well in the image feature extraction session.

The algorithm in the paper is based on the VGG neural network, which is widely used and its performance can be comparable to manual in image recognition processing capability. The algorithm applies VGG19 network, which contains 16 convolutional layers, 5 pooling layers, and does not use fully connected layers. At the same time, in order to synthesize the output image and make the image more infectious, the algorithm uses average pooling instead of maximum pooling to complete the optimization of gradient flow. At the same time, the algorithm defines a set of nonlinear filters on each layer of the convolutional network, whose complexity varies with the position of the convolutional layer in which they are located. The algorithm transforms the traditional cultural symbols of the reference image to the input image and finally synthesizes a new image that has both the content of the input image and the style of the reference image.

The VGG19 network actually starts with an image consisting of an image with white noise and passes through the constraints of two loss functions, i.e., content loss function and style loss function. Eventually, an image with the color and artistic style of the reference image is generated.

3.2. Target Content Map Contour Extraction

Style migration based on traditional cultural symbols first extracts the edge contours of traditional cultural symbols and then fills them with different saturated color textures so as to simulate real traditional cultural symbols using the edge contours of the target content map.

The target image contours are extracted in order to identify the parts of the data image where the brightness of the local area varies greatly.Canny edge detection is an algorithm that uses multilevel edge detection to identify as many actual edges of the image as possible. At the same time the identified edge contours are more accurate with the actual image.Canny algorithm is a multistage edge detection algorithm which consists of 4 main steps.

Gaussian filtering smoothes the image. Due to the imaging process, by the components and circuit structure, signal transmission process and other factors, will inevitably produce image noise, these noises will reduce the image quality, interfere with the effect of edge detection, resulting in an increase in the results of pseudo-edge.Canny edge detection algorithm in the removal of noise in the gray-scale image $f(x,y)$ in the Gaussian filtering method, the filtered image is $g(x,y)$. The two-dimensional Gaussian function is:

$$G(x,y)=\frac{1}{2\pi\sigma^2}\exp(-\frac{x^2+y^2}{2\sigma^2}) \tag{1}$$

where: σ is the standard deviation.

Calculate the gradient magnitude and direction. If you want to perform edge detection, you need to get the image gradient information, Canny algorithm uses the first-order difference operator to calculate the gradient direction and magnitude of the pixel point. The mathematical expression of the bias matrix in the horizontal and vertical 2 directions is:

$$T_x=\frac{[g(x,y+1)-g(x,y)+g(x+1,y+1)-g(x+1,y)]}{2} \tag{2}$$

$$T_v=\frac{[g(x,y)-g(x+1,y)+g(x,y+1)-g(x+1,y+1)]}{2。} \tag{3}$$

The computation of pixel gradient magnitude $M(x,y)$ and gradient direction θ using Eq. (2) and Eq. (3) are shown in Eq. (4) and Eq. (5), respectively:

$$M(x,y)=\sqrt{T_x^2+T_y^2} \tag{4}$$

$$\theta=\arctan(T_y/T_x) \tag{5}$$

Non-Great Value Suppression. After obtaining the gradient direction and magnitude of each pixel point of the image, a non-great value suppression operation is performed on the pixel gradient magnitude to find possible edge points in the image. The specific method is to determine whether the gradient magnitude of a pixel point is the largest among the surrounding ones having the same gradient direction, and if not, set the gray value of the point to zero, and conversely retain the point as a candidate edge point.

Hysteresis threshold detection. After the above steps, most of the actual edges of the image can be detected relatively accurately, but at this time may be incorrectly retained part of the pseudo-edge, if you want to further determine the true boundary, you need to filter out the pseudo-edge and other cases through the high and low double threshold. Specific operation: when the gray gradient of the image is higher than the high threshold is considered to be the true edge, if lower than the low threshold points will be discarded. If it is between the two, it is necessary to further determine the situation of the pixel points in its 8 fields, if there is a true edge point in its 8 fields, the point will be retained, otherwise it will be deleted.

3.3. Target Content Map Contour Line Enhancement

The edge contour map generated above by Canny algorithm has thin and discontinuous lines, while the real content image has low background saturation and distinct contrast features with the foreground. Therefore, morphological methods are used to expand the image to enhance the edge contour lines of the image. The content map line features are simulated by operations such as closure operation and expansion, and the morphological operation is calculated as shown in equation (6):

$$R(x,y) = B(x,y) \oplus S + A((B(x,y) \cdot S)) \tag{6}$$

where: $B(x,y)$ is the content map edge contour image, $\oplus$ is the morphological expansion operation, $\cdot$ is the morphological closure operation, and A is the resultant image after line contour enhancement.

3.4. VGG-19 model optimization

In order to better adapt to the characteristics of different traditional cultural symbols, the target content map contours are detected. Firstly, extract the style and content of the selected traditional cultural symbols separated and fused by the VGG-19 model to provide new ideas for dress design. Secondly, search for traditional cultural symbols images. Finally, images with traditional cultural symbols are generated. The model is applicable to the style migration of different clothing elements, which provides the possibility of diversification and interest of clothing elements. The process of style migration image generation is shown in Figure 1, and the process of style migration is mainly divided into the following five steps.

(1) Randomly input an initialized white noise textile image.

(2) The white noise textile image is input into the VGG-19 optimization network model to calculate the loss function.

(3) Calculate the gradient of the loss function with respect to each pixel.

(4) Fine-tune each pixel value.

(5) Continuously iterate and fine-tune each pixel value to obtain a more complete style migration image.

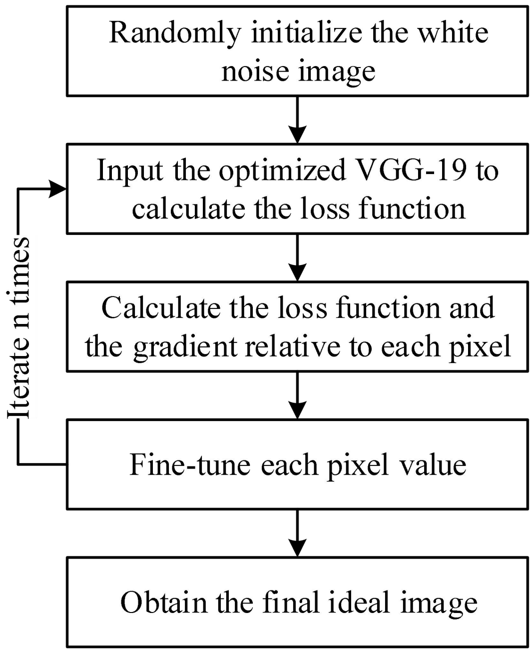

Figure 1. The generation process of the style migration image.

3.4.1. Content Loss Function

In the VGG-19 optimization model, the content loss function measures the content difference between two images by comparing the difference between the output result feature maps of the content image and the generated image at a certain layer. First, the content image is input to a certain convolutional layer of this model to derive a generation result, and then the generation image is input to the same convolutional layer to derive a generation result, and the obtained two generation results are differed, squared, and summed element-by-element as the content loss function $L_{content}(\vec{p},\vec{x})$, and the computation of the content-generated image of this model is shown in Equation (7):

$$L_{content}(\vec{p},\vec{x}_0,l)=\frac{1}{2}\sum_{i,j}(F^l_{i,j}-P^l_{i,j})^2 \tag{7}$$

where $L_{content}(\vec{p},\vec{x},l)$ is the content loss at layer 1, $\vec{p},\vec{x}_0$ are the content image and white noise image respectively, i is the i th feature map, j is the j th value on the feature map, and $F^l_{i,j}$ is the value of the lth layer of the feature map after inputting the generated image optimized from white noise into the VGG-19 model, and $P^l_{i,j}$ is the value of the 1st layer of the feature map after inputting the content map into VGG-19, which is usually a constant. The content loss function can be biased against the feature value $F^l_{i,j}$ of the generated map to obtain the activation derivative (8) for layer l as follows:

$$\frac{\partial L_{content}}{\partial F^l_{ij}}=\begin{cases}(F^l-P^l)_{ij} & if \quad F^l_{ij}>0\\ 0 & if \quad F^l_{ij}<0\end{cases} \tag{8}$$

The closer the feature map is to P^l, the smaller the difference between the two is, and the content loss function is 0 when the two values are equal.

3.4.2. Style Loss Functions

In addition to the content loss function mentioned above to preserve the contours of the content image, likewise the style loss function utilizes the VGG-19 model to extract the stylistic texture and marginalization information of the image, thus ensuring that a complete stylistic characterization of the target image is obtained. The style loss function usually represents the texture information of the image synthesis in terms of Gram matrix (GM), which represents the style of an image in terms of co-occurrence correlation between features rather than spatial pixel information values.The GM matrix is represented by the inner product of the eigenvalues of any layer in the VGG-19 optimization model with the eigenvalues of the transpose matrix as shown in equation (9):

$$G^l_{ij}=\sum_k F^l_{ik}F^l_{jk} \tag{9}$$

Assuming that the output style features of layer 1 are taken, $\vec{g}$ and $\vec{x}$ denote the original and generated maps, and $\hat{G}^l_{ij}$ and G^l_{ij} are the layer 1 styles where w_l denotes the weight that layer 1 takes in the total loss, the style loss function and the total loss function of the layer can be calculated as shown in Eq. (10) and Eq. (11):

$$E_l=\frac{1}{4N_l^2M_l^2}\sum_{i,j}(G^l_{ij}-\hat{G}^l_{ij})^2 \tag{10}$$

$$l(\vec{g},\vec{x})=\sum_{l=0}^{L}W_lE_l \tag{11}$$

where: N_l is the number of channels and M_l is the product of the aspect of the feature map.

Each layer has different weights, and the style loss function of each layer is multiplied with the weights of the corresponding layer and then weighted and summed to get the final style loss function. Through several iterations, to judge whether the final result is idealized, then back propagation and gradient descent are performed to find out the gradient of the style loss function with respect to the original generated image element, and each pixel value is continuously adjusted to minimize the style loss function and output the best ideal style migration image.

3.4.3. Style Migration Image Generation

The VGG-19 optimization model is equivalent to a feature extractor, and the results extracted by the middle layer of the model measure the content of the generated image. Comparing the content map features with the generated map features yields a content loss function, and the style loss function uses the features to compute the image GM matrix, thus comparing the GM matrix of the style map with the GM matrix of the generated map to measure the style difference, yielding a style loss function. In the total loss function, the content loss function reflects the content difference between the content map and the generated map, and the style loss function expresses the style difference between the style map and the generated map, as shown in equation (12):

$$L_{total}(\vec{p},\vec{a},\vec{x}) = \alpha L_{content}(\vec{p},\vec{x}) + \beta L_{style}(\vec{a},\vec{x}) \tag{12}$$

where: α and β are weight coefficients different for content and style, $\vec{p}$ is the content image, $\vec{a}$ is the style image, and $\vec{x}$ is the generated image.

4. Experimental Results and Analysis

4.1. Data Sets

In this paper, the clothing style images are from Microsoft Common Objects in Context (MS COCO) dataset, of which a total of 9,000 images were selected for the style migration dataset, 7,500 for the training set, and 1,500 for the test set.

Experimental environment: CUDA11.1, deep neural network library version 8, the operating system is Centos7.6, the graphics card is NVIDIA GeForce V100 32 G, equipped with the open-source framework for deep learning Pytorch 1.12, programming language Python3.8.

4.2. Model Training

Multiple sets of samples are selected for validation, and it is found that the loss decreases as the number of training times increases. When the number of training times exceeds 250, the training loss tends to stabilize, and increasing the number of training times will not reduce the training loss. Considering the training efficiency, the number of epochs in the training of this paper is chosen to be 250 times. The training convergence curve of the model is shown in Figure 2, and the number of iterative training reaches more than 150 times and gradually stabilizes.

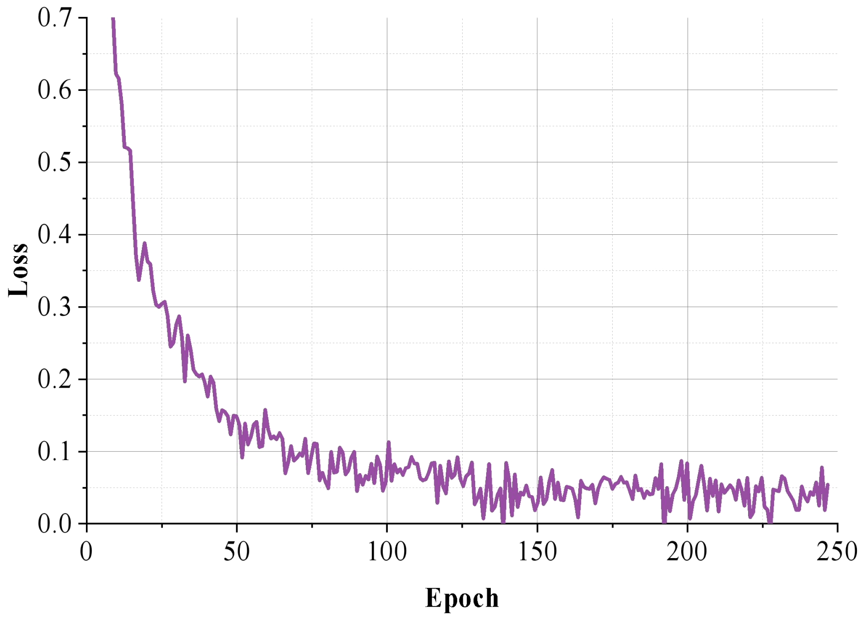

Figure 2. The training convergence curve of the model.

4.3. Assessment of Indicators

The recognition of the effect of clothing image migration in addition to some objective discriminatory observations, but also need to analyze the indicators as a further support. In this paper, the more common indicators are selected for the evaluation of the recognition effect in this paper, including the mean square error, peak sex-to-noise ratio, structural similarity and style migration speed. The details are as follows:

a) Mean Square Error [MSE]: a common key indicator of recognition performance, mainly used to compare the difference between the true value and the predicted value, the smaller the value indicates the better the recognition performance.

b) Peak Sexual Noise Ratio [PSNR]: mainly measures the difference and quality between two images.

c)Structural Similarity [SSIM]: is used to assess the degree of similarity between two images.

d)Style Migration Speed [STS]: mainly assesses the style migration efficiency of the method, which is an important evaluation index of the method, that is, it calculates the time consumption of this paper's method in comparison with other methods for recognition.

4.4. Experimental Results

4.4.1. Ablation Experiments

In this paper, (1) VGG-19, (2) VGG-19 for target content map contour extraction, (3) VGG-19 for target content map contour line enhancement, (4) VGG-19 for target content map contour extraction and line enhancement, and (5) Optimized VGG-19 algorithm for target content map contour extraction and line enhancement are subjected to ablation experiments in terms of the root-mean-square error of the outputs, peak signal-to-noise ratio and speed of style migration are compared, and the metrics evaluation results under the ablation experiment are shown in Fig. 3. The root mean square error of this paper's clothing image style migration method based on traditional cultural symbols has decreased compared with other methods, and the decrease is more than 18.68%, and the peak signal-to-noise ratio is also higher than other methods, with a PSNR of 24.46, which is a big improvement in image performance and quality, and the style migration speed is 8.63, which is lower than other methods. Therefore, this paper's method can improve the visual effect of the garment migration image as well as the efficiency of the style migration speed is higher than other methods, which indicates the feasibility and effectiveness of this paper's method.

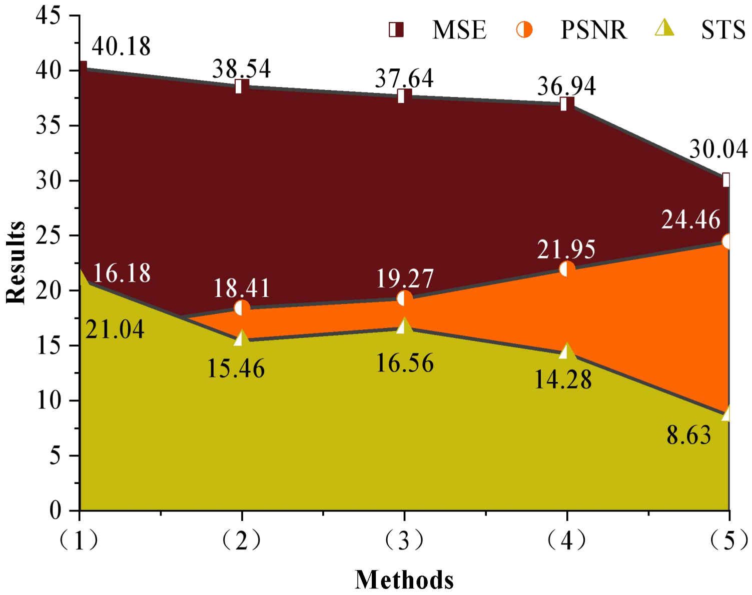

Figure 3. Evaluation results of indicators under ablation experiments.

4.4.2. Assessment of Indicator Results

In this paper, FCN method, VGG-19 method, Cyclegan method, Cyclegan_loss method are mainly selected to compare with the improved VGG-19 method in this paper, and the quality of each method is evaluated by using the above indexes, and the evaluation results of the indexes under each method are shown in Fig. 4. Overall the performance of this paper's method is good, in the index PSNR, SSIM are presented the maximum value, respectively, 18.58 and 0.86, indicating that this paper's method of image migration quality and structural similarity are higher, the root mean square error is close to the Cyclegan_loss method, but the overall difference is small. In terms of style migration speed this paper's method is the fastest with an STS value of 3.74, which is highly efficient. Therefore, the method in this paper performs well in style migration of garment images, with higher image quality and clarity, as well as being closer to the original style map.

In this paper, the peak signal-to-noise ratio is selected to measure the image quality and difference, and after comparing with other methods, it is found that: the improved VGG-19 method in this paper has the largest peak signal-to-noise ratio, which is improved by 5.09% and 9.62% compared with the Cyclegan_loss method and the Cyclegan method, and the signal-to-noise ratio is even more than 20% compared with the VGG-19 method and the FCN method. It can be seen that the migrated image generated by the improved VGG-19 method based on traditional cultural symbols in this paper has clear edge texture, high image quality, good style integration, and can meet the basic needs of virtual clothing design.

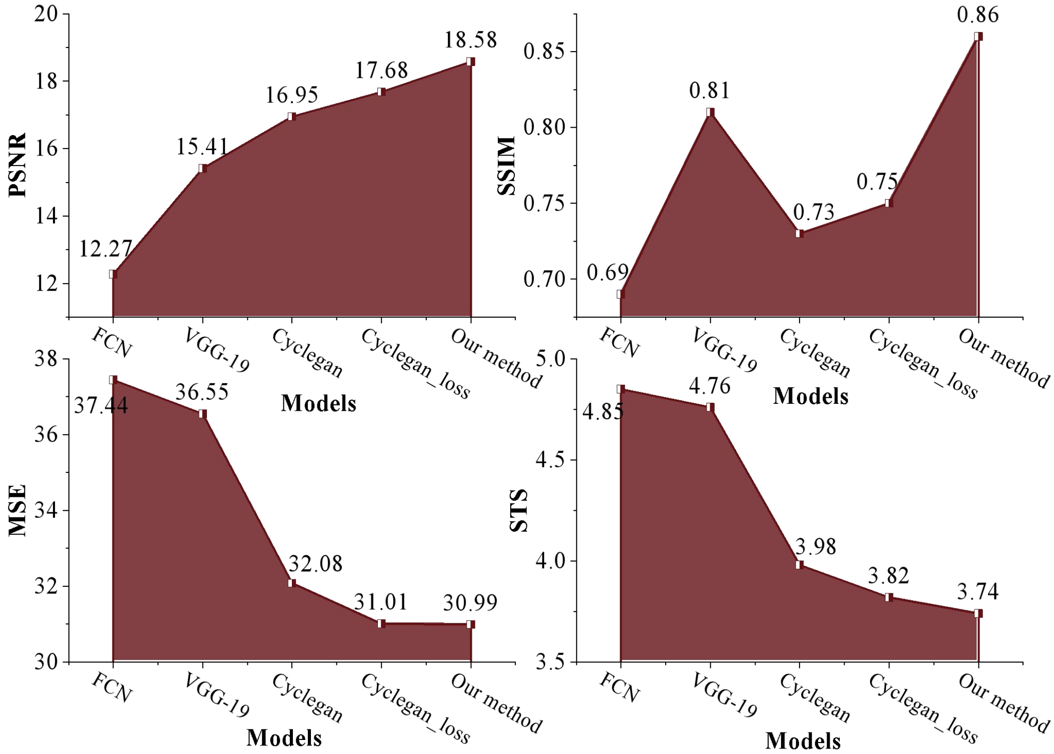

Figure 4. Evaluation results of indications under each model.

4.4.3. Analysis of Methodological Applicability

In order to verify the effectiveness of the algorithm, five groups of experimental images containing traditional cultural symbols (celadon style, New Year's painting style, Dunhuang mural style, Miao embroidery style and mounted into the style) and the generated resultant images are made into a survey chart, and 120 teachers and students majoring in computer and clothing design are collected in a university for a questionnaire survey, and the results of the survey for the three questions are shown in Fig. 5 to Fig. 7. The questions are as follows:

Question 1: Which rendering better demonstrates the effect of style migration in terms of texture and color?

Question 2: Which rendering has done a better job of promoting intangible cultural heritage and artistic rendering?

Question 3: Which rendering did a better job in terms of creativity?

More than 49% of the respondents thought that the texture and color of the celadon porcelain had a better migration effect. 35% of the respondents thought that the New Year's Paintings style did a better job of promoting intangible cultural heritage and had a better artistic rendering effect. 39% of the respondents thought that the Dunhuang Mural style did a better job of creativity. The results of the survey reflect to some extent that this paper supports the design and creative work of clothing designers in the migration of clothing styles as well as the selection of materials.

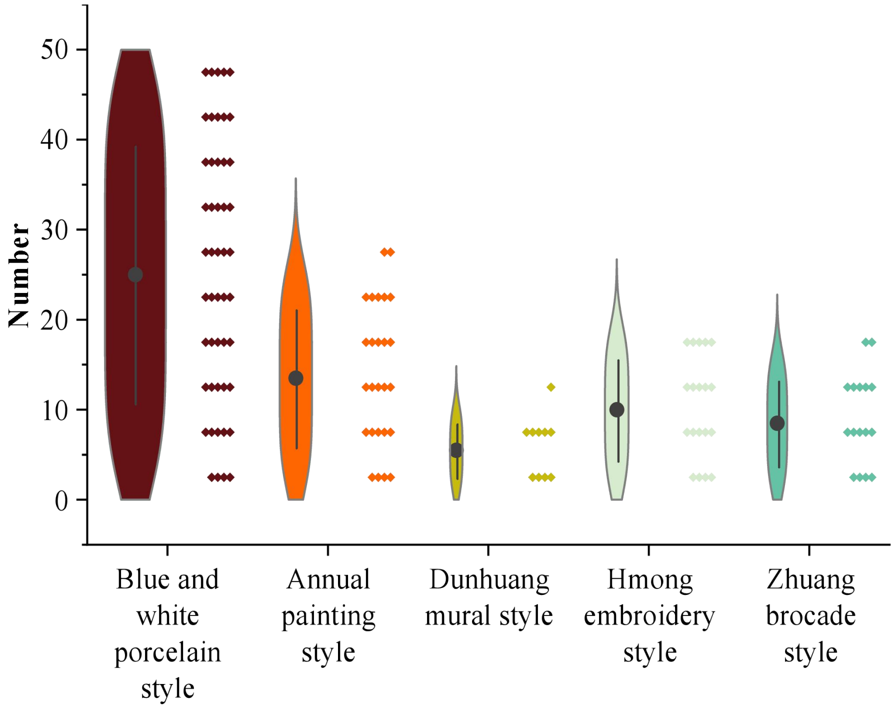

Figure 5. The respondent Support results of the question one.

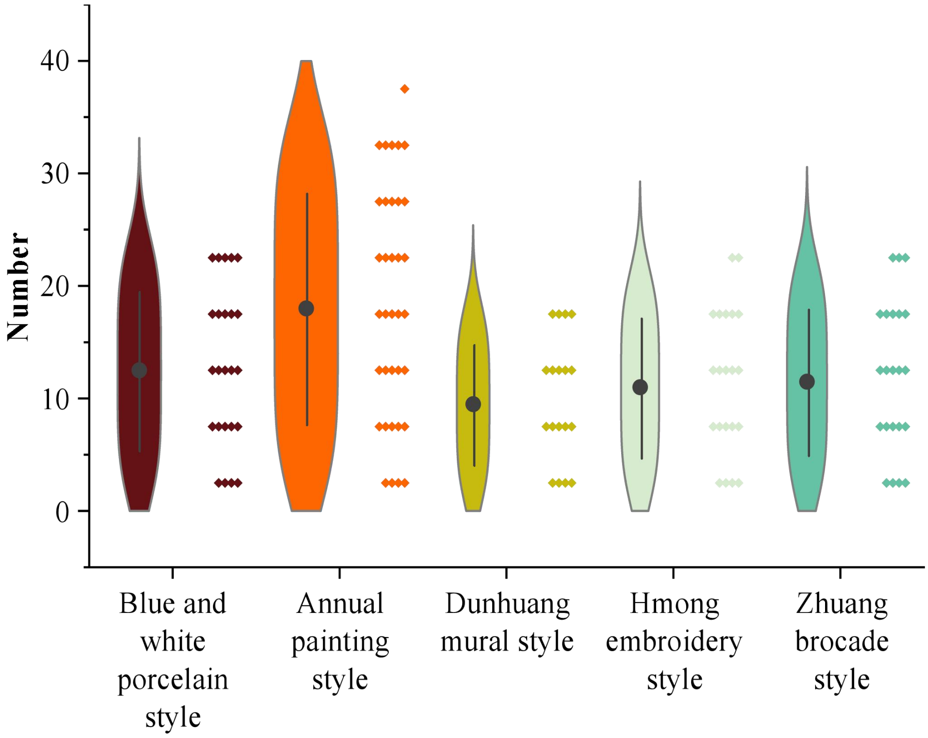

Figure 6. The respondent Support results of the question two.

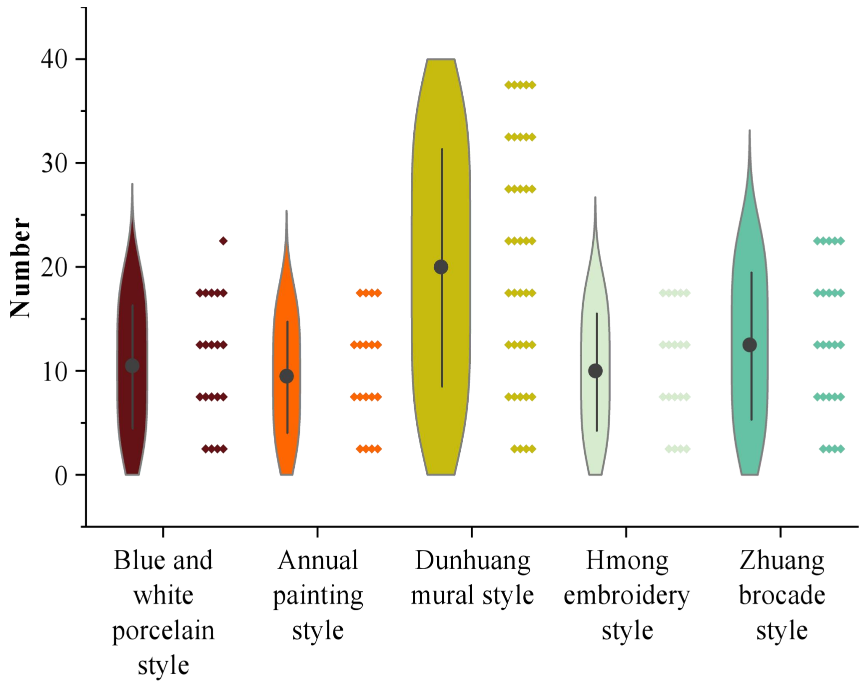

Figure 7. The respondent Support results of the question three.

5. Conclusion

The research is based on the application of computer vision technology in the display of intangible cultural heritage, optimizing the VGG-19 algorithm, constructing a style migration model for clothing images, and proposing a virtual clothing design method based on traditional cultural symbols. Experiments are carried out to evaluate the proposed style migration method, and the main research results are as follows:

(1) In the ablation experiment, the root mean square error of this paper's method decreases by at least 18.68% compared with other methods, and the peak signal-to-noise ratio and the style migration speed are 24.46 and 8.63, respectively, which are better than the comparison method, reflecting the effectiveness of this paper's target content map contour extraction, contour bar enhancement, and optimization of the VGG-19 model. In the comparison experiments, the PSNR and SSIM values of this paper's method are larger than those of other methods, and the root mean square error and style migration speed are smaller than those of other methods, in which the PSNR value is improved by 51.43%, 20.57%, 9.62%, and 5.09% compared with FCN, VGG-19, Cyclegan, and Cyclegan_loss algorithms, respectively, which indicates that this paper's method generates style migration images with high quality and clarity, closer to the original image style.

(2) Among the clothing images generated using traditional cultural symbols migration, 49% of the personnel believe that the celadon style has a better application effect on the texture and color of clothing design, 35% of the personnel believe that the artistic rendering effect of the New Year's painting style is better, while 39% of the personnel agree with the migration effect of Dunhuang frescoes on the clothing design creativity. The experiment shows that the style migration model based on the improved VGG-19 in this paper can be used in the integration of traditional cultural symbols and virtual clothing design.

In the subsequent research, it is proposed to carry out stylization from the whole to the part of the garment, and realize the stylization of a certain region of the garment, so that the stylization method of the garment can be used more flexibly. The features as well as the loss function in the process of style migration are optimized to enhance the effect of the generated style migration map.The VGG-19 network has a large number of layers, and the selection of model parameters as well as the trade-off of network layers will be improved in the following.

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