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Digital Reconstruction and Innovative Representation of Ningbo Mud-Gold Color Paint Images of National Intangible Cultural Heritage in 3D Clothing Design

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SUMMARY: *As a national intangible cultural heritage, Ningbo Mud-Gold Color Paint, with its exquisite craftsmanship and historical and cultural values, occupies an important position in Chinese traditional crafts, and also provides rich inspirations for modern clothing design. This paper constructs a 3D reconstruction model based on Transformer-MVSNet and proposes a fast garment migration network method with multi-style fusion, so as to realize the digital reconstruction of Ningbo Mud-Gold Color Paint images and the innovative design of garments. The study shows that the accuracy difference and overall error of the Transformer-MVSNet model are 0.312mm and 0.339mm, respectively, which is better than other methods in terms of overall error and second only to CVP-MVSNet in terms of accuracy difference, with better comprehensive performance. Moreover, under the same resolution, the memory consumption and running time of the Transformer-MVSNet model are always less than those of other models, realizing high accuracy under low consumption. In addition, the clothing style migration model in this paper outperforms other comparative models in five metrics, including Inception Score (IS), Mode Score (MS), Frechet Inception Distance (FID), Wasserstein Distance, and Maximum Mean Difference (MMD). This paper provides an example for digital reconstruction and innovative design of intangible cultural heritage.*

KEYWORDS: *Ningbo Mud-Gold Color Paint lacquer; style migration; clothing design; Transformer; MVSNet*

1 Introduction

At present, the "Chinese trend" has a profound impact on Chinese clothing design style, and the application of Chinese excellent traditional cultural elements in the field of fashion is getting more and more attention [1]. In the traditional wedding trousseau of Ningbo area, there is a traditional decorative craft - Ningbo Mud-Gold Color Paint (Fig. 1), which plays a significant role in the decorative patterns. These traditional motifs have a wide range of topics, in general, the pattern design of Ningbo Mud-Gold Color Paint lacquer mainly focuses on the expression of auspicious symbolism, which supports the parents' expectations and wishes for the future of their children's good life, reveals a strong folklore, and transmits a good expectation [2]. Therefore, with its unique artistic charm and deep cultural heritage, the patterns presented by Ningbo Mud-Gold Color Paint lacquer techniques provide a rich source of creativity for modern clothing designers

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Figure 1: Ningbo traditional wedding customs:Bride, Wangong sedan, Furniture, Trousseaux, Wedding procession

In the rapid development of information technology today, Digital manufacture technology is widely used in various industries, it is the main force to promote industrial upgrading and product innovation [3, 4]. At the same time, the use of digital technology has gradually penetrated into the field of apparel design, and 3D apparel modeling technology has become the main design and production tool, and the popularization of this technology promotes the development of apparel industry in the direction of high technology, and helps to promote the technological upgrading of apparel industry [5, 6]. In 1990, MIRALAB Laboratory released the “FlashBack” project, which means that the research work on digital garments has officially begun. With the continuous development of digital technology, digital clothing has been developed to the extent that it can present the appearance and texture of clothing in a realistic way, and to a certain extent, it can verify the accuracy of the clothing pattern [7].

Traditional culture and science and technology are complementary, you can deeply excavate the connotation and aesthetic value contained in traditional culture, combine with modern science and technology, and constantly innovate the tradition, and this method of excavation and combination is a crucial step in the innovation process [8-10]. By transforming the tradition and adding modern aesthetics, it is innovatively pushed forward to meet the current social needs [11]. With the continuous development of society, intangible cultural heritage is widely used in the fields of handicrafts [12], architecture [13], clothing [14], etc., especially in the field of clothing design has become more and more mature. Intangible cultural heritage can be used as a material inspiration library in the creative process of clothing brands, highlighting the integration of traditional culture and clothing design, and adding unique artistic value and cultural connotations to clothing [15]. Incorporating the pattern of Ningbo Mud-Gold Color

Paint lacquer into the 3D design of clothing is not only an innovative attempt to pass down this non-heritage skill, but also an important way to promote its revitalization in the modern society. The innovative use of Ningbo Mud-Gold Color Paint lacquer patterns in 3D clothing design can not only bring many creative inspirations for clothing designers, but also provide a new perspective and practice for the protection and innovative development of intangible cultural heritage.

Academic research on China's intangible cultural heritage costume design has a wide range of results, and has a fairly high level in terms of depth and breadth, including research on the reproduction and restoration of traditional costumes, as well as the integration of intangible cultural elements into modern costume design, etc., but there is a lack of research on the combination of Ningbo Mud gold colored lacquer and costume design [16, 17]. Qi et al. used computer clothing design and virtual reality technology to digitally convert non-heritage garments, through the identification and segmentation of non-heritage garments, such as style, color, and texture features, to achieve the data capture, storage, and reproduction of clothing information, which is of great significance to the protection of non-heritage culture [18]. Cai et al. explored the intangible cultural heritage-bamboo weaving technology, integrated into the innovative design of clothing from multiple perspectives, and analyzed the economic and environmental benefits it brings to the clothing industry, which contributes to the organic fit between intangible cultural heritage and the field of fashion, and also has guiding significance for the dissemination of intangible cultural heritage [19]. Zhang, Y et al. combined Baikuyao's traditional clothing with modern clothing design methods, i.e., they integrated Baikuyao's prints, patterns and other cultural symbols in the creation of modern clothing, and designed clothing with a unique ethnic culture and in line with modern fashion [20].

In addition, Chen, J visited the She region in Fujian, China to understand the local traditional embroidery craft in depth, and tried to integrate it with clothing design and carry out related courses to cultivate innovative talents combining traditional handicrafts and fashion, so that the traditional culture can be inherited in an innovative way [21]. Pan et al. used an electron microscope to excavate the symbolic artistic connotation of Ming and Qing porcelain in terms of depth, pattern, material, and color, while analyzing the feasibility of porcelain in modern clothing design by drawing and innovating patterns on porcelain symbols to provide material for modern clothing design [22]. Chen, K et al. explored a new strategy for the dissemination of Teochew embroidery in apparel design by combining Teochew embroidery craft and cultural elements with modern apparel design concepts, and then developing creative apparel fashion products through Digital Intelligence technology to realize the innovative dissemination of Teochew embroidery culture [23]. Ke et al, on the other hand, conducted a field study on the inheritance logic of China's intangible cultural heritage in apparel design, and the survey found that some of the intangible heritage bearers lacked the spirit of innovation, and designed intangible apparel products that could not reach the aesthetic level of today's consumers, which highlighted the importance of the intangible cultural heritage innovation [24].

At present, the development of 3D apparel modeling technology is relatively mature and occupies a large market share, and the mainstream apparel modeling software includes Style 3D, Marvelous Designer, etc., which provide better design platforms for apparel designers, so that they can transform their ideas into actual products faster, and save time and cost [25, 26]. In recent years, academics have conducted in-depth research and made progress on 3D design for apparel. ZIFEI et al. visualized and analyzed 1,532 related articles and designed a related literature knowledge map to provide a systematic overview of the current status, shortcomings and challenges of 3D apparel design, and they pointed out that 3D apparel design is the key development trend of the apparel field in the future [27]. Porterfield et al. incorporated 3D garment simulation into the garment design and production process and gathered different perspectives from experts, garment designers and garment manufacturers in the form of interviews in order to create a highly coordinated 3D garment design framework [28]. Ji et al. proposed a three-dimensional interactive design scheme based on wedding dress clothing, first obtain the human body three-dimensional model through three-dimensional scanning, and then carry out the three-dimensional style design of the wedding dress, and verify the effect of the wedding dress physical generation in the virtual simulation platform, and the generated 3D wedding dress model has a better performance both in terms of fit, comfort and design efficiency [29]. Choi et al. used a 3D virtual simulation system to establish a 3D dynamic apparel design platform integrating multiple styles, colors, and patterns, and professional apparel designers and digital technology experts recognized the potential of this platform's application in apparel design [30].

In addition, Cao, C et al. used virtual reality technology to realize the 3D design of traditional clothing, obtained the characteristic data of human body through curve fitting method, according to the styling and structural characteristics of cheongsam, and established the 3D model of cheongsam clothing in Marvelous Designer clothing simulation software [31]. Cao, Y et al. tried to use CLO3D technology for the structural design of ethnic clothing after deep understanding of the structural characteristics of Chinese ethnic clothing and achieved very good results, which can be combined with the artificial intelligence fitting room and other technical software to further proliferate the application of digital intelligence technology in the field of clothing [32]. Chen, A et al. on the other hand, designed the Lingnan grass weaving intangible cultural heritage clothing 3D generation system, the system through the collection of the customer's human body information using the principles of biogenetics for the design of clothing styling, and then the use of 3DS MAX technology three-dimensional visualization of clothing styling [33]. Zhang, X et al. applied 3D virtual clothing design technology to the design of intangible cultural heritage (ICH) plant dye clothing, which realized the digital reproduction of ICH and provided a new direction for the protection of plant dye clothing, which was able to achieve efficient dissemination [34].

The purpose of this paper is to explore how to extract and apply the Ningbo Mud-Gold Color Paint lacquer images to 3D clothing design, in order to realize the organic combination of traditional cultural elements and modern design technology, and to provide new perspectives and practical paths for the inheritance and integration of traditional crafts in modern clothing design (Fig. 2). Combining MVSNet and Transformer model, and using grouped SDTA encoder, a digital reconstruction model of Mud-Gold Color Paint images based on Transformer-MVSNet is proposed. On this basis, a fast garment migration network method that integrates multiple stylistic features such as texture, pattern, and color of clay and gold paint images is proposed. Meanwhile, in order to verify the effectiveness of the method in this paper, experimental verification is carried out respectively. In the upcoming chapters, we delve deeper into these topics. To begin, we will present an overview structure of MobileViT involved, including MV2 Module and MobileViT block, in the initial section of this paper. Subsequently, in the second section, we will elaborate on the overall structure of our improved fine-grained image classification method and three strategies. Furthermore, we will demonstrate the effectiveness and superiority of our method through rigorous experiments in the third section. Finally, we provide a comprehensive summary of the entire paper

Figure 2: Ningbo mud-gold painted lacquer image extraction in 3D

2 Digital Reconstruction of Ningbo Mud-Gold Color Paint and Innovative Path of Clothing Design

2.1 The past and present life of Mud-Gold Color Paint lacquer

Ningbo Mud-Gold Color Paint is a kind of craft that combines Mud craft and Gold Color craft as the main feature, and paints, stacks, applies gold and colors on the wooden lacquer embryo. Ningbo lacquer is a traditional folk art of Ninghai County, Ningbo City, Zhejiang Province. On May 23, 2011, Ningbo lacquer was approved by the State Council of the People's Republic of China to be included in the third batch of national intangible cultural heritage list. The history of Mud-Gold Color Paint is very long, dating back to the Hemudu period, more than 7,000 years ago, and the red wooden lacquer bowls unearthed at the Hemudu ruins are similar to the production of Mud-Gold Color Paint. However, the first official record of Mud-Gold Color Paint was made in China during the Ming Dynasty, when it was at its peak of production.

2.2 Subject matter and symbolism of clay-gold colored lacquer patterns

The decorative themes and compositional features of Ningbo Mud-Gold Color Paint are mainly inherited from the Ming and Qing Dynasty, with auspiciousness as the core, highlighting the expectations of peace, wealth, health and happiness, and showing the warm and joyful folklore of good fortune and prosperity (Fig. 3). The motifs are rich and varied, including auspicious decorations, figures of gods and goddesses, characters and opera stories, life styles, plants and animals, landscapes, auspicious words, etc. The compositional arrangement shows the quiet and elegant style of Jiangnan.

Figure 3: Ningbo mud-gold lacquerware features some pattern theme: Childlike Fun illustration, Singing birds and Fragrant flowers, Dragon and Phoenix, Carp frolicking in water

2.3 Digital reconstruction and innovation of Mud-Gold Color Paint lacquer images

2.3.1 Digital reconstruction of Mud-Gold Color Paint lacquer images

(1) Image Recognition and Segmentation Technology

Image recognition and segmentation technology is a key step in realizing the extraction of artistic elements of emblem carving. This technology can automatically identify the key elements in the image, such as lines, patterns, colors, etc., and segment the image into multiple segments, while accurately separating the key elements from the background to achieve accurate identification, thus providing high-quality materials for subsequent design applications.

(2) Feature extraction and coding technology

After identifying the elements of Mud-Gold Color Paint lacquer, feature extraction and coding techniques are further utilized for in-depth analysis of these elements. The feature extraction technology can identify the unique form, texture and color characteristics of the elements, while the coding technology converts these characteristics into computer-understandable digital forms. This process not only preserves the original aesthetics of the Mud-Gold Color Paint lacquer elements, but also provides the possibility of their re-creation in the digital environment. In this paper, we realize the extraction of image features and three-dimensional representation by three-dimensional reconstruction of Ningbo Mud-Gold Color Paint lacquer artifact images.

2.3.2 Innovative design of garments with clay-gold colored lacquer images

(1) Artistic style migration

The style migration and generation technology is able to migrate the unique style of clay paint images into clothing design works, or generate new elements with the style of clay paint images according to the instructions of clothing designers. Through the training of the deep learning model, the style migration and generation technology can realize the accurate capture and reproduction of the style of the clay paint images, which provides a rich source of creative materials and inspiration for fashion designers.

(2) Dynamic effects and interactive design

In addition to static image elements, it is also possible to transform the Mud-Gold Color Paint lacquer image elements into dynamic effects, such as animation, video and so on. By combining computer graphics and animation technology, dynamic elements with the style of clay paint images can be generated, thus providing more attractive visual effects for clothing design. In addition, interaction design can be carried out using AIGC and other technologies, enabling designers to flexibly adjust the size, position, color and other attributes of the elements to achieve a more flexible and personalized design effect.

3 Digital Reconstruction of Ningbo Mud-Gold Color Paint Images

This chapter combines MVSNet with Transformer and uses a grouped SDTA encoder instead of the original Encoder part, and proposes a Transformer-MVSNet 3D reconstruction model to realize the digital reconstruction of Ningbo Mud-Gold Color Paint images.

3.1 Transformer-MVSNet 3D reconstruction modeling

3.1.1 MVSNet network architecture

The scene depth information prediction network (MVSNet) is a network model for scene depth information prediction.The MVSNet model algorithm flow is as follows:

(1) Feature extraction: the MVSNet uses CNN to extract the deep learning features of multi-view images in the feature extraction stage. Assuming the input image is L, the feature extraction module can be expressed as:

$$F(L) = \{ f_1, f_2, \ldots, f_n \} \tag{1}$$

where f_i denotes the feature vector of the i th image.

(2) Construction of cost volume: in the process of cost volume construction, MVSNet projects the virtual camera on the reference camera cone by indistinguishable uni-responsive transformation, so as to construct the 3D cost volume, and realize to encode the camera parameters and image information together. The cost volume can be expressed as:

$$C(x,y,d) = \sum_{i=1}^{n} w\left(f_i(x,y), f_i(x-d,y)\right) \tag{2}$$

where x, y are the pixel coordinates, d is the parallax, w is the weight function, and $f_i(x,y)$ and $f_i(x-d,y)$ are the feature vectors.

(3) Depth map generation: in the depth map generation stage, MVSNet utilizes multi-scale convolutional neural network and 3D convolutional neural network modules to realize high-precision depth map generation. Among them, the multi-scale convolutional neural network can be expressed as:

$$D(x,y) = \sum_{K=1}^{K} \alpha_k D_k(x,y) \tag{3}$$

where D_k denotes the depth map at different scales, α_k are the weight coefficients, and K are the scale weights.

The 3D convolutional neural network can be represented as:

$$D(x,y) = \sigma\left(\sum_{C=1}^{C} \theta_C * C(x,y,c)\right) \tag{4}$$

where * denotes the convolution operation, $C(x,y,c)$ is the slice of the cost volume at channel C, θ_C is the convolution kernel corresponding to channel C, and σ is the nonlinear activation function.

(4) Depth map aggregation: In the depth map aggregation stage, MVSNet uses a novel

aggregation strategy to integrate multiple depth maps into an accurate 3D point cloud representation. The aggregation strategy can be expressed as:

$$P(x,y)=\frac{\sum_{K=1}^{K}\omega\left(D_k(x,y)D_k(x,y)\right)}{\sum_{K=1}^{K}\omega\left(D_K(x,y)\right)} \tag{5}$$

where P is the point cloud coordinates, D_k is the different depth maps, and ω is the weight function, which can be defined as:

$$\omega(d)=\frac{1}{1+(a\,|\,d-b)^{c}} \tag{6}$$

where a, b and c are constants to control the shape of the weight distribution.

3.1.2 Improved MVSNet network

(1) The overall structure of the network

The flow of the multi-view 3D reconstruction system based on deep learning constructed in this paper is shown in Figure 4. The input of the system is a collection of views of Ningbo Mud-Gold Color Paint lacquer crafts in different viewpoints. In this paper, the input image is first preprocessed, and the inner and outer parameters of the camera can be calculated by the motion recovery structure algorithm, and then the sparse point cloud model is obtained from the calculated parameters, and the depth sampling value is determined by the sparse 3D point cloud model. Next, this paper constructs a deep learning network for stereo matching of multiple views, through which the depth map corresponding to each view can be estimated, and finally the dense 3D reconstruction model can be recovered through the depth map.

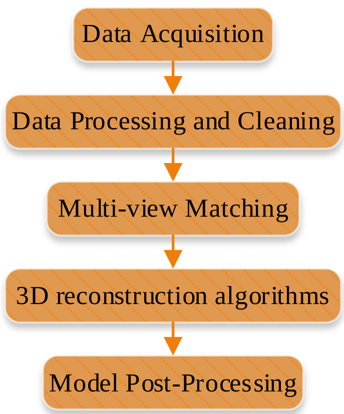

Figure 4: Multi-view 3D reconstruction process

In this paper, the grouped SDTA encoder module is used for feature extraction in the stereo matching part. Dynamic multi-scale feature fusion is performed first, where different number of branches are used to fuse the information in different stages of the network. In stages 2, 3 and 4, the number of channels of the input features are equally divided into 2, 3 and 4 ways. 3*3 denotes 3*3 depth divisible high convolution, when the number of channels is 3 or 4, the information of the input 3*3 convolution is derived from the convolutional output information of the previous branch and the information of this channel. Finally, the feature layers of multiple branches are spliced in the channel dimension, so the number of channels of the input and output feature layers remains the same. The output features of each channel are calculated as:

$$y_i = \begin{cases} x_i & i=1 \\ d_i\left(x_i\right) & i=2, t=2 \\ d_i\left(x_i+y_{i-1}\right) & 2<i\le s \end{cases} \tag{7}$$

where d denotes the depth-divisible high convolution, x_i denotes the i th feature layer of the input feature layer after splitting, and y_i denotes the output of the i th branch.

The STDA Encoder is divided into two main sub-modules when the input is a 4D tensor of (N, C, T, H, W): Spatial Temporal Attention (STA) and Dynamic Aggregation (DA).

1) STA module

The STA module consists of two main parts: a spatio-temporal convolutional layer and a spatio-temporal attention layer.

In the spatio-temporal convolution layer, a joint convolution layer consisting of spatial convolution and temporal convolution is used. The size of the temporal convolution is $k_t \times 1 \times 1$, where k_t denotes the window size of the temporal convolution. And the size of the spatial convolution is $1 \times k_h \times k_w$, where k_h and k_w denote the height and width of the spatial convolution, respectively. This joint convolution layer is shown below:

$$X'_{i,j} = \sum_{n=0}^{k_t-1} \sum_{h=0}^{k_h-1} \sum_{w=0}^{k_w-1} W_{n,h,w} X_{i,j+n,h,w} \tag{8}$$

where X denotes the input data, X' denotes the convolution result, and W denotes the convolution kernel.

The spatio-temporal attention layer is mainly used to capture the cross-attention information of the input data in spatial and temporal dimensions. Suppose $X' \in R^{N*C*T*H*W}$ is the input to the STA module, where N denotes the batch size, C denotes the number of channels, T denotes the number of time steps, H and W stand for the height and width of the spatial dimensions, respectively, and d_{model} denotes the vector spatial dimension of each head. We first pass a matrix transformation on the input tensor, spreading the last two dimensions to obtain a 3D tensor X'' with shape $(N \times H \times W) \times T \times C$. The transformed input data is fed into a multi-head attention mechanism, which consists of h multi-heads with d_k-dimensional output vectors in each group.

In the multi-head attention mechanism, the attention score can be computed by three matrix transformations, Q, K and V. In the multi-head attention mechanism, the attention score can be computed by three matrix transformations, Q, K and V, respectively. Where Q, K and V denote the query, key and value of the multi-head attention mechanism respectively, which are calculated as follows:

$$Q = X''W^Q; K = X''W^K; V = X''W^V \tag{9}$$

where $W^Q \in R^{C*d_k h}, W^K \in R^{C*d_k h}$ and $W^V \in R^{C*d_v h}$ are the three momenta. d_k and d_v are the vector space dimensions of each head, and h is the number of heads.

Then, we can splice together the results obtained from the multi-head attention mechanism and get the output of the multi-head attention layer through a matrix transformation in the shape of $R^{(N*H*W)*T*C}$.

2) DA module

The DA module is implemented by using grouped convolution, global maximum pooling, ReLU activation function and dropout layer. Assume that the output of the multi-head attention layer is $O \in R^{(N*H*W)*T*C}$, where T denotes the time step. Eventually, the representations of all groups are stitched together in the shape of $R^{(N*H*W)*T*D}$, where D is the sum of the dimensions of these groups.

(2) Introduction of SENet module

The core idea of SENet module is to learn the correlation between each channel and filter out the important features through the channel-specific attention mechanism, so as to improve the performance of the network. The implementation process of SENet module is shown in Fig. 5:

1) Sequeeze operation

The dimension of the input feature map is $W*H*C$. With the global pooling operation, each position of the feature graph is treated as a fully connected layer operation with the same weight and the entire feature graph is compressed into a single value.

2) Excitation operation

The excitation operation consists of two fully connected layers and two activation functions, after a series of operations, the dimensions of the input features and the dimensions of the output features are not changed.

3) Scale operation

Scale operation is to merge the original features with the features after the attention mechanism to get the final feature matrix.

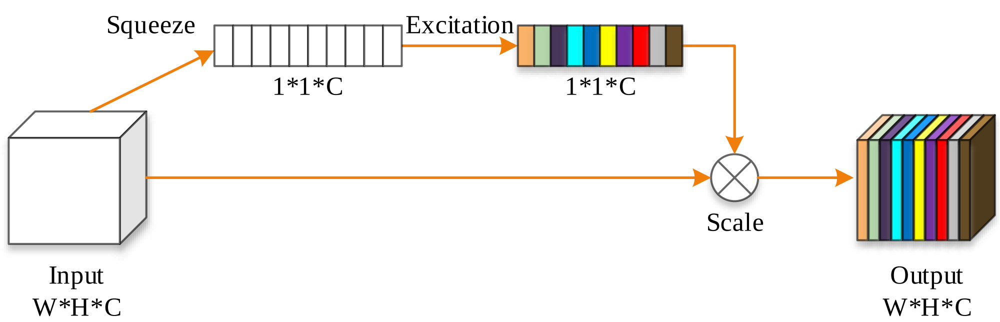

Figure 5: SE attention module

SKNet structure is the product of SENet combining SEopetator, Merge-and-Run Mappings and attention on inception block.SKNet structure is shown in Fig. 6. In this paper, SKNet structure is improved and 3D-SKNet structure is proposed, which is introduced in t, w and h dimensions respectively, so as to fully extract the features of each channel.

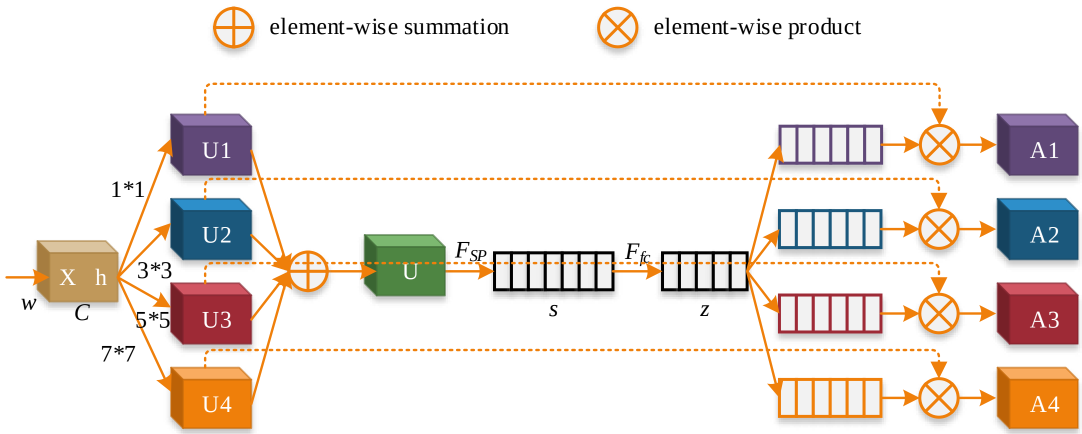

Figure 6: Selective Kernel Convolution

(3) Global feature extraction based on Transformer

This paper introduces the Transformer module, which is capable of associating more feature points, sequentially establishing long-distance dependencies, extracting richer features, and improving the model's ability to capture global features.

3.2 Experimental results and analysis

3.2.1 Experimental environment

To ensure the validity and comparability of the algorithms, all the experiments in this chapter are conducted in the same configuration, using a server for training and testing. The experimental environment configuration parameters are shown in Table 1.

Table 1: Experimental environment configuration parameters

Experimental environment	Parameter
Operating system	Ubuntu 24.04
Graphics card	ASPEED Graphics Family 12G video memory
Memory	32GB
Processor	Intel(R) Xeon(R) CPU E5-2640 v4 @ 2.40GHz
Programming languages and frameworks	python 3.12.5, torch 1.8.1
Related libraries	torchvision, opencv-python, numpy, plyfile, pillow, tensorboard, Delaunay

3.2.2 Experimental data sets

In order to solve the possible problems of reflections, no texture, and repeated texture in the image reconstruction of Ningbo mud-gold colored lacquer, this study forms the first three-dimensional reconstruction dataset of mud-gold colored lacquer artifacts based on the basics of stereo vision by photographing 150 different mud-gold colored lacquer artifacts with 7 different types of illumination from 50 precise camera positions, and at the same time performs precise structured-light scanning. Ten types of 150 different Mud-Gold Color Paint lacquer artifacts were collected, totaling 37,500 images, of which, 33,750 were training and 3,750 were testing.

3.2.3 Experimental results

The experiments use a robust training strategy in selecting source and reference views by randomly selecting N-1 (N<12) of the 12 optimal source views for training. This scheme increases diversity during training and dynamically enables data augmentation to improve algorithm generalization performance, and training on random source views with weak correlation improves robustness for algorithm visibility estimation.

By alleviating the occlusion problem, the accuracy of reconstruction can be improved by using more views, then the accuracy of the Transformer-MVSNet model for N=2~8 is shown in Table 2. It can be seen that the more the number of views to some extent, the reconstruction accuracy and overall error rate are improved. However, at N=6 is the better overall performance, then 6 views input is used in this algorithm.

Table 2: Reconstruction accuracy with different bumbers of sheets

N	Precision difference (mm)	Overall error (mm)
2	0.442	0.395
3	0.438	0.367
4	0.435	0.362
5	0.426	0.357
6	0.426	0.352
7	0.429	0.358
8	0.438	0.363

In order to examine the performance of the Transformer-MVSNet model in this paper, in this section, we take 1600×1200 size, 6 image inputs at a time, set the depth range $[350mm, 850mm]$, and reconstruct the image by MVSNet , R-MVSNet, CVP-MVSNet, DLPMNet, and Transformer-MVSNet algorithms for comparative experiments, and the reconstruction results of each model are shown in Table 3.

Using qualitative and quantitative analysis, the results show that the accuracy difference and overall error of Transformer-MVSNet are 0.312 mm and 0.339 mm, respectively, which is better than the other methods in terms of overall error, and second only to CVP-MVSNet in terms of accuracy difference, with better overall performance.

Table 3: Reconstruction results of each model

Algorithm	Precision difference (mm)	Overall error (mm)
MVSNet	0.415	0.571
R-MVSNet	0.396	0.432
CVP-MVSNet	0.304	0.364
DLPMNet	0.367	0.413
Transformer-MVSNet	0.312	0.339

In addition, comparing the completeness of the reconstruction results, this paper finds that the Transformer-MVSNet algorithm is significantly denser and more concentrated than the other model point clouds, and the completeness and overall quality are better than the other models, which is due to the fact that the Transformer-MVSNet introduces the SDTA encoder structure and the SKNet structure for the feature extraction, thus better extracting the long-distance information in the data, so the reconstruction effect in texture and boundary is better, and the accuracy of 3D reconstruction is higher, thus providing a more realistic and rich visual experience.

In order to verify the comprehensive performance of this algorithm, the memory consumption and runtime are compared with several mainstream deep learning-based advanced methods, which achieve strong performance in terms of low memory consumption and runtime, and since MVSNet, R-MVSNet consume more serious memory and runtime, then CasMVSNet, UCSNet, CVP- MVSNet, DLPMNet and other algorithms that are closer to the running time and memory consumption of this network for experimental comparison, each model is inputted with the same dataset of images and bit positions, and the optimal parameters after training with self-constructed dataset are used, and the results of their running time and memory consumption are averaged. The relationship between the running time and resolution of each model is shown in Fig. 4, and the relationship between memory occupation and resolution is shown in Fig. 5.

Combining Figures 7 to 8 shows that when the number of depth assumptions is fixed, the memory and runtime of all methods increase almost linearly with resolution, resulting in insufficient spatial sampling of the zoomed image by the cost-volume methods used. At higher resolutions, the memory consumption and runtime of Transformer-MVSNet grows more gently. That is, at the same resolution, the memory consumption and running time of the Transformer-MVSNet model are always less than the other models. Also from Table 3, although Transformer-MVSNet is second only to the CVP-MVSNet model in terms of accuracy difference, in terms of overall error, Transformer-MVSNet reduces by 6.87% compared to CVP-MVSNet, and compared to the other models, it reduces by 14.99%~ in terms of accuracy difference and overall error, respectively. 24.82% and 17.92% to 40.63%, respectively. In summary, the Transformer-MVSNet algorithm is effective and has excellent overall performance than other deep learning based methods.

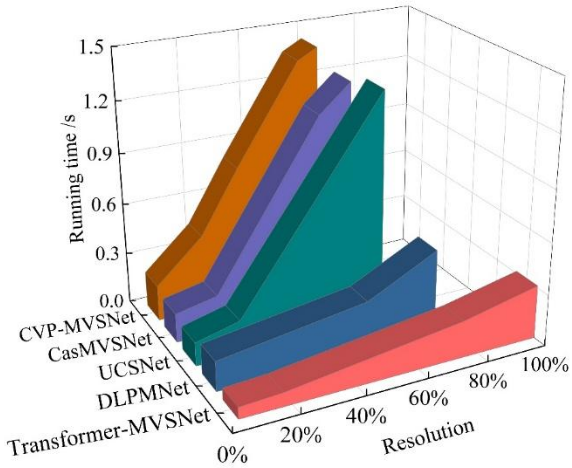

Figure 7: Relationship between model running time and resolution

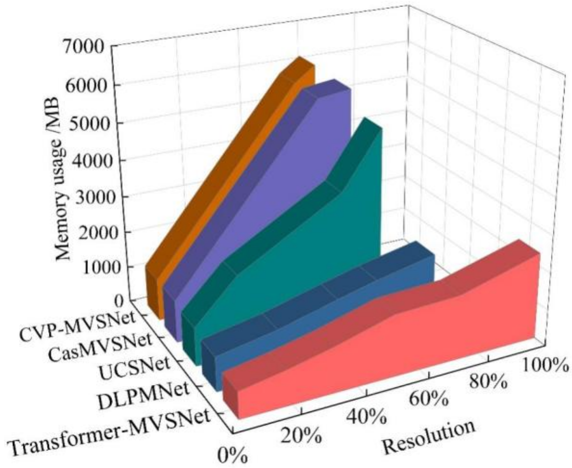

Figure 8: Relationship between model memory usage and resolution

4 Innovative design of clothing based on the migration of Mud-Gold Color Paint lacquer image styles

Based on the digital reconstruction of Ningbo Mud-Gold Color Paint lacquer images, this chapter proposes a fast garment migration network method with multi-style fusion as a way to realize the innovative design of garments based on Mud-Gold Color Paint lacquer images.

4.1 Overall Framework of the Clothing Style Migration Model

This chapter proposes a fast clothing style migration deep network model as shown in Fig. 9, which is designed with a multi-style fusion pre-training network, which can fuse multiple Mud-Gold Color Paint image style elements, such as pattern, texture, and color, into one clothing style element, and realize the fusion of multiple styles. At the same time, four kinds of semantic loss functions are designed for the characteristics of texture, outline, color, and material of the clothing, which makes the migrated texture material more realistic, the pattern motif clearer, and the clothing outline prominent and obvious.

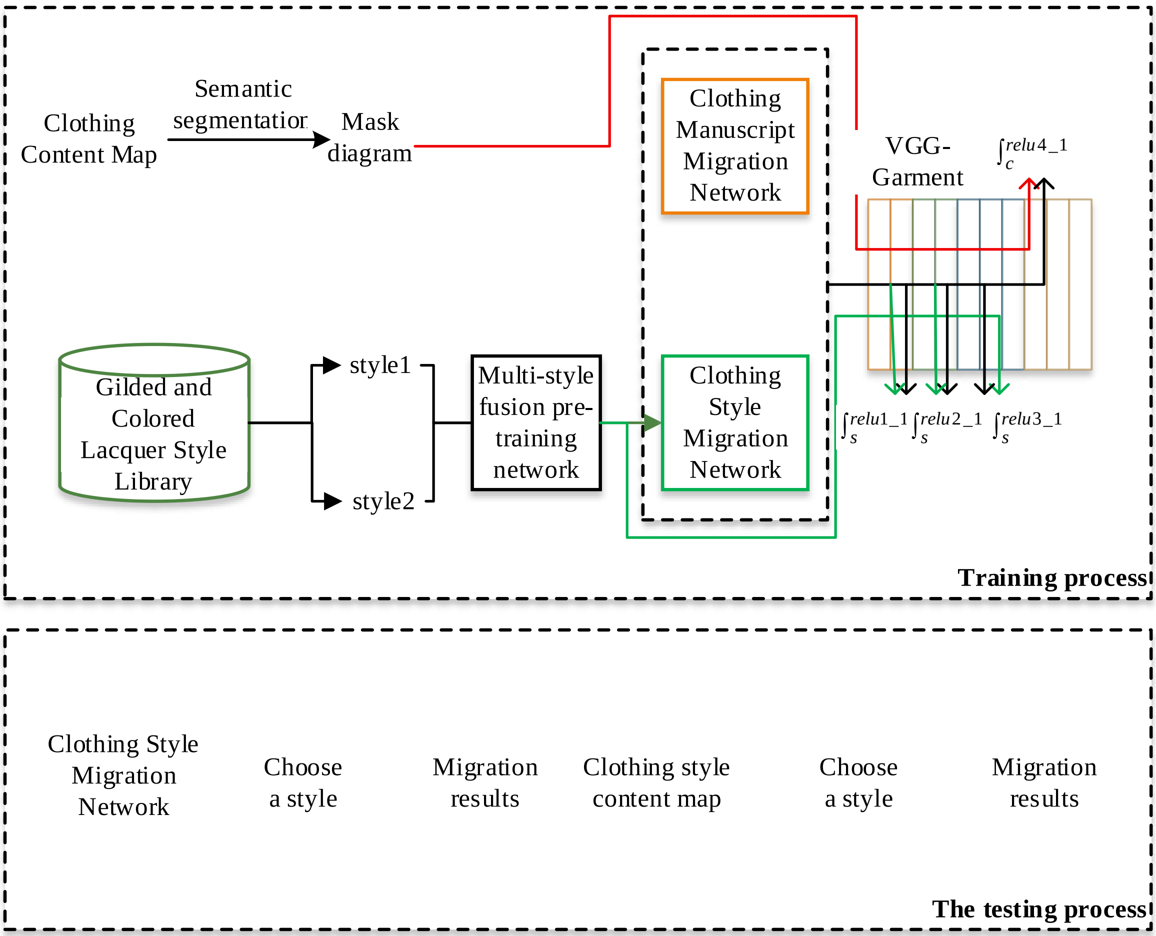

Figure 9: Overall framework of the clothing migration model

4.2 Clothing Outline Extraction

One of the differences between garment image migration and generic image migration is the need to ensure that the outline of the garment image is clear and the content outside the outline of the garment does not need to be migrated in a stylized manner, so here the target region needs to be identified and segmented.

In this paper, in order to accurately segment the target region and generate the mask image, MASK-RCNN is used, and Faster-RCNN is used as the main framework, and another parallel branch of FCN is introduced at the head of the network, which is used for detecting the mask image information of ROI, where ROI is the region to be segmented. Firstly, the garment content map is input to get the bounding box of the garment image, the feature maps in the selection box are extracted using ResNeXt-101+FPN, and the ROL of the generated feature maps are transformed to a fixed ROL. The output global features are then resized to the prescribed size with dimension 512, filled twice using pooling layer, and then classification and boundary regression are performed. Simultaneously and in parallel, a binary mask is output for each Rol, and a mask is predicted for one based on each Rol, and finally multiple convolution operations are performed during mask generation using the following equation:

$$l = l_{mask} + l_{ds} + l_{box} \tag{10}$$

where L_{cls} is the classification error, L_{box} is the detection error, and L_{mask} is the segmentation error. Here the classification error is the relative entropy for each pixel using the Sigmod function to find the average relative entropy error is, the classification error is the logarithmic loss calculated for each Anchor, and then summed and divided by the total number of Anchors to get the classification loss, and the segmentation error calculates the average regression error for each RoI.

4.3 Garment Migration Network

4.3.1 Network structure

In this paper, the clothing migration network is composed of multi-style fusion pre-training network and clothing manuscript migration network, after the MASK-RCNN network extracts the outline of the clothing, in this chapter, we use the multi-style fusion pre-training network to fuse a variety of Mud-Gold Color Paint image styles, and migrate the content images to the migration network after inputting the content images into the migration network, and migrate the material of the Mud-Gold Color Paint images such as color, texture, pattern and so on to a piece of clothing at the same time.

The structure of the multi-style fusion network is shown in Fig. 10. The training process of the network is by inputting two image pairs of clothing style elements, the features of the Mud-Gold Color Paint image elements are extracted as the clothing style elements, and the VGG-Garment network is used as the loss network to calculate the style loss, and finally the multi-style fusion pre-training network is obtained after training, and the output of the clothing element fusion map is obtained.

s_1' and s_2' obtained after the convolution operation of s_1 and s_2, where s_1' is uniquely hot coded as $(1,0,0\ldots), s_2'$ is uniquely hot coded as $(0,1,0\ldots)$, where the uniquely hot coding is a one-bit valid coding with an element value between 0 and 1, and each clothing style element map represents the uniquely hot coding with one element of 1 and the rest of 0, where w is the weight and M is the matrix, which is fused to y_s after the fusion of the multi-style fusion pre-training network, which is defined by the computational form as follows:

$$y_s = M\left[(1-w)s_1' + ws_2'\right] \tag{11}$$

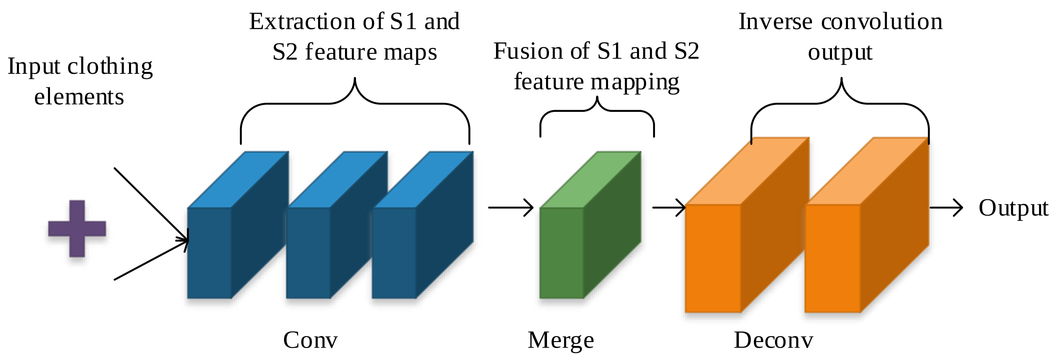

Figure 10: Multi-style pre-trained model

In order to migrate the clothing element styles to the clothing content map, this paper constructs a clothing migration network, which includes a manuscript migration network and a clothing style network.

The clothing manuscript migration network has five convolutional layers and one inverse convolutional layer, the first layer of the convolutional layer uses a convolutional kernel with a step size of 1, the fusion layer is a convolutional kernel with a step size of 2, and after that there are three residual blocks and three layers of convolutional layers, the convolutional layer uses a convolutional kernel with a step size of 2, and then four inverse convolutional kernels with a step size of 2 are utilized to improve the quality of the output migrated result image. Considering that it is a localized migration and does not require excessive network capacity, this chapter is constructed using convolutional layers in the first layer to extract the spatial features of the apparel content map and the apparel style map.

In order to generate the clothing content map with style features, the second layer uses a fusion layer to fuse the feature maps and the tandem mask matrix, and the third to fifth layer's use a convolutional layer to deeply process the fused image. In order to obtain a clear garment style migration map, the last layer is constructed using an inverse convolutional layer. In the training process, the clothing content map and clothing style map are input, the feature maps are extracted and fused respectively, and the loss function is calculated using VGG-Garment network to obtain the clothing manuscript migration network.

4.3.2 Loss function

The following different loss functions are defined in this chapter.

(1) Content loss function:

$$L_{cont}^{\psi,j}(\hat{y}, y_c) = \frac{1}{H_j W_j C_j} \left\| \psi_j(\hat{y}) - \psi_j(y_c) \right\|_2^2 \tag{12}$$

where $\psi_j(y)$ denotes the feature map of the content map at the j th layer of the convolutional neural network, and H_j, W_j and C_j denote the height, width, and the number of channels of the features at the j th layer, respectively. $\hat{y}$ is the output image and y_c is the input garment content map. The square normalized Euclidean distance between the output image and the input image is used to determine the similarity of the content structure between the migrated image and the apparel content map, and the smaller the Euclidean distance is, the closer the generated result is to the content of the original content map.

(2) Style loss function:

To make the output image $\hat{y}$ consistent with the style features of the style element y_c, this paper proposes the clothing style loss function, which utilizes the VGG-Garment network to discriminate the content consistency between the output clothing image and the clothing style map, therefore, the clothing style loss function of the j th layer is expressed as follows:

$$\varphi = C_j \times H_j \times W_j \tag{13}$$

C_j is the number of channels, H_j, W_j are the height and width of the features, respectively, and φ denotes the feature image of $C_j \times H_j \times W_j$.

The $G_j^{\varphi}\left(\hat{y}_{target}\right)$ is the homogenization of the non-central covariance of the c_j -dimensional features, and also represents the corresponding Gram matrix $\hat{y}_{target}$ as the garment region of the output:

$$G_j^{\varphi}\left(\hat{y}_{target}\right) = \phi\phi^T / C_j H_j W_j \tag{14}$$

The stylistic consistency between the output and the target image can be determined by the Euclidean distance between the output of the Gram matrix and the target image, from which Eq. (14) can be extrapolated to derive Eq. (15) using Eq:

$$L_{l-style}^{\psi,j}\left(\hat{y}, y_s\right) = \left\| G_j^{\psi}\left(\hat{y}_{target}\right) - G_j^{\psi}\left(y_s\right) \right\|^2 \tag{15}$$

(3) Color loss function

In order to ensure that the migration style color remains consistent, this paper proposes a color loss function, through the VGG-Garment network calculates the mean and variance on the color space, to achieve the selected color elements and the output results of the same color, the calculation form is as follows:

$$L_{colar} = \frac{\sigma_c}{\sigma_s}\left|\hat{y} - y_s\right| \frac{1}{H_j W_j} \tag{16}$$

where σ_c and σ_s are the standard deviation and variance of the output versus the style element maps, $H_j W_j$ represents the height and width of the feature maps at the j th layer, and $\hat{y} - y_s$ is the color gap between the output and the style maps in RGB space. .

(4) Contour Loss Function

In order to maintain the migration output of the clothing contour, this paper adopts the contour complementation algorithm to define the clothing contour loss function as:

$$L_{line} = \frac{1}{|N|}\sum\left|\hat{y} - y_c\right|^2 \tag{17}$$

where N is the set of all pixels in the image, and $\hat{y}-y_c$ is the calculated mean square deviation of the output image from the input content.

In summary, the fast clothing migration loss function formula constructed in this chapter is defined as:

$$L=\lambda_C L_{l-cont}^{\psi,j}\left(\hat{y},y_c\right)+\lambda_s L_{l-style}^{\psi,j}\left(\hat{y},y_s\right)+\alpha L_{line}+\beta L_{color} \tag{18}$$

Among them, four parameters are set to regulate the weights, which are clothing content loss λ_ε, clothing style loss function λ, clothing silhouette weights α, and clothing loss weights β.

4.4 Model application experiments

In this section, the experimental validation of the clothing style migration model proposed above will be carried out to show the effectiveness and superiority of the model on the clothing design task oriented to the style migration of Mud-Gold Color Paint images through evaluation metrics.

4.4.1 Experimental data sets

The experiment uses 8000 images from MS COCO 2014 as the content image dataset, and the style images are selected from the clay-gold colored lacquer style images that are more typical of the stylistic features in the previous studies on digital reconstruction, and each image is resized to 256×256 size, with the Batch Size set to 16, and the training is optimized by using Adam and setting the The learning rate is 10^{-3}.

4.4.2 Experimental evaluation indicators

For generating images, although a person can evaluate the quality of them by naked eyes, this process is too subjective, so several reasonable evaluation indexes need to be introduced. In this paper, Inception Score (IS), Mode Score (MS), Frechet Inception Distance (FID), Wasserstein Distance, and Maximum Mean Difference (MMD) are introduced as evaluation indexes. Among them, the larger IS and MS are, the better the model is. And the smaller FID, Wasserstein distance, and MMD are, the higher the quality of the model is.

4.4.3 Analysis of experimental results

Given the three-dimensional images of Mud-Gold Color Paint lacquer and the images of clothing manuscripts, the fast clothing migration network model of multi-style fusion proposed in this paper is used to model the innovative use of Mud-Gold Color Paint lacquer images in clothing design. The experimental results show that the model in this paper can migrate the texture, pattern, color and other styles of the Mud-Gold Color Paint lacquer images to the clothing style images.

Comparing this paper's model with MSGNet, WCT, SANet, FeedS, AdaAttN and other models, it is found that the other models do not have the function of local style migration, and can only obtain the effect image generated by global style migration. In order to better compare the effect of clothing style migration, the global clothing style generation is first performed on the clothing manuscript image, and then the top area of the generated image is cut out according to the clothing manuscript image, and finally it is covered to the top area of the clothing style image to get the final effect image. From the visual effect comparison, the model in this paper is better than the other models in terms of the adequacy of the style migration of the Ningbo

Mud-Gold Color Paint images as well as the details of the generated styles.

The generated images of each comparison model are evaluated using common evaluation indexes such as IS, MS, FID, Wasserstein distance, MMD, etc., and the results of the evaluation of each model index are shown in Table 4. It can be seen that the evaluation values of this paper's clothing style migration model on the five indicators of IS, MS, FID, Wasserstein, and MMD are 1.903, 0.905, 0.495, 359.432, and 0.435, respectively, which are better than the other comparison models.

Table 4: Index evaluation results of each model

Model	IS↑	MS↑	FID↓	Wasserstein↓	MMD↓
MSGNet	1.894	0.669	0.533	760.457	0.997
WCT	1.495	0.017	0.752	857.462	0.806
SANet	1.552	0.029	0.737	925.823	0.945
FeedS	1.723	0.161	0.672	747.438	0.998
AdaAttN	1.827	0.303	0.565	754.004	0.944
Methods in this chapter	1.903	0.905	0.495	359.432	0.435

In this paper, local style loss and local content loss are introduced into the model to ensure the consistency in content and style between the Mud-Gold Color Paint lacquer craft images and the generated garment images. In order to further verify the effectiveness of local style loss and local content loss, this paper takes the image texture style as the object, and uses the peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), mean square error (MSE), universal quality index (UQI) and multi-scale structural similarity index (ME-SSIM) to measure the texture similarity between the original Mud-Gold Color Paint lacquer artifacts images and the generated clothing images. The texture similarity between the original Mud-Gold Color Paint lacquer artifact image and the generated garment image is obtained, and the experimental results of local style loss and reconstruction loss ablation are shown in Table 5. The experimental results show that the method in this paper can effectively improve the generation quality of mud-gold paint texture in the generated garment images, and compared with the original global style loss, all the metrics in PSNR, SSIM, MSE, UQI and ME-SSIM are optimized, and the relative optimization magnitude reaches 7.38%, 60.20%, 36.24%, 34.09%, respectively, 126.96%.

Table 5: Results of the ablation experiment

	PSNR↑	SSIM↑	MSE↓	UQI↑	ME-SSIM↑
Global style loss	29.126	0.608	101.659	0.657	0.319
Partial style loss	29.357	0.962	97.428	0.853	0.712
Partial style loss + Partial content loss	31.274	0.974	64.815	0.881	0.724

5 Conclusion

In order to realize the digital reconstruction of Ningbo mud-gold colored paint images and apply them to the field of clothing design, this paper constructs a 3D reconstruction model Transformer-MVSNet and a fast clothing migration network model with multi-style fusion, and examines the effectiveness of the model.

When the number of views N=6, the reconstruction accuracy and overall error rate of the Transformer-MVSNet model are small, and the comprehensive performance is better. Comparing with MVSNet, R-MVSNet, CVP-MVSNet, and DLPMNet models, the

Transformer-MVSNet model is optimal in terms of overall error, and second only to CVP-MVSNet in terms of poor accuracy, with better overall performance. In addition, at higher resolutions, the memory consumption and running time of Transformer-MVSNet increase more gently compared with other models, indicating that the Transformer-MVSNet model can realize lower memory consumption and running time with higher accuracy at the same resolution.

In terms of evaluation indexes such as IS, MS, FID, Wasserstein distance, and MMD, the evaluation values of this paper's clothing style migration model are 1.903, 0.905, 0.495, 359.432, and 0.435, respectively, which are better than those of other comparison models. Meanwhile, compared with the original global style loss, this paper's model with the introduction of local style loss and local content loss is optimized in terms of PSNR, SSIM, MSE, UQI, and ME-SSIM, and the relative optimization is 7.38%, 60.20%, 36.24%, 34.09%, and 126.96%, respectively. In addition, an experience satisfaction survey of users found that more than 80% of users believed that they had a better process experience when using this paper's model for creative pattern design of clothing compared to the GAN-based style migration method. Only a small portion of the users of this paper's model generated by the creative pattern of clothing does not match their own aesthetic orientation, and thus the next stage should be carried out to ensure that the creative pattern of clothing generated by the Ningbo Mud-Gold Color Paint images is in line with the public's aesthetics.

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