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Innovative Design of Traditional Ethnic Clothing Based on Numerical Computing Optimization Combined with Smart Wearable Devices

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ABSTRACT

Using digital back camera to complete the traditional national costume image acquisition work, and then with the help of VOLO model to segment and colorize the image, the traditional national costume elements were successfully extracted. By fusing them with smart wearable devices, a detailed fusion implementation scheme is developed, which contains constraints and objective functions. In the context of numerical computation optimization, the fruit fly algorithm (FAO) is used to explore the fusion design scheme of the two in depth. The values of the four objective factors of the fusion design are 0.233, 0.232, 0.348, 0.144, and the final value of the objective function is 0.957, which indicates that the results of this paper not only can improve the comfort of the device and the user's experience, but also can provide a new idea and method for the fusion of the apparel industry and the wearable device industry.

Keywords: numerical computation optimization, Drosophila algorithm, VOLO model, traditional ethnic clothing, wearable devices

1. Introduction

Traditional culture is the source of design inspiration in many industries, such as advertising, clothing and literature and many other fields. Along with the development of cross-cultural communication and globalization, traditional elements have been respected and welcomed in the world, and traditional culture has been effectively combined with the world's clothing trends [1]. Chinese culture is rich and diversified, which can give great inspiration to the design of clothing, the appropriate use of traditional elements in clothing design, and through the modernization of the way to achieve the combination of trends and traditions, can to a large extent to add the characteristics of the clothes, and even give the clothing a new meaning, and at the same time, to convey the cultural self-confidence [2-3]. The concept of national costume design is to integrate the traditional elements of national culture

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into modern fashion, highlighting the unique style and personality of the nation, and at the same time conveying the unique charm and values of national culture. The innovation of clothing design is not only expressed in style, technology and color matching, but also in connotation and culture. Nowadays, the design of traditional national costumes will pay more attention to the protection and inheritance of traditional culture, and at the same time, combine with modern design concepts and technology to create costumes that are more in line with the aesthetic needs of modern people. Through the integration of tradition and modern technology, ethnic clothing will be more adapted to the lifestyle and needs of modern people and continue to develop in the field of fashion [4-6].

In this paper, we first complete the traditional national dress image acquisition work with the help of digital back camera, and perform GROT hybrid feature coding, reconstruction jump connection, and multi-scale up-sampling fusion on the image to realize traditional national dress image segmentation and get the image without background. Subsequently, the encoder and decoder of GrDbUNet are used to recolor this image to eliminate the color difference between it and the original image. After the above series of graphic processing work, the traditional national costume elements are successfully obtained. Then, starting from the definition and characteristics of smart wearable devices, the fusion design scheme of smart wearable devices and traditional national costumes is proposed, which consists of constraints, objective function and Drosophila optimization solution algorithm. Borrowing data analysis tools, the fusion design of the two is explored and analyzed, aiming to promote the integration and development of the clothing industry and wearable device industry.

2. Overview

The innovation of traditional national costumes is the innovation of design concept on the one hand, and the innovation of design technology on the other hand.Cheng and Qingxiang [7] innovated the design concept of national costumes, and they proposed to combine the modern aesthetics and performance techniques with traditional costume elements and regional culture, so as to make the classic and the times converge with the inheritance and innovation. With the development of emerging technologies, the innovation of traditional costumes has ushered in vitality, Zhang and Liu [8] called for the need to add new techniques and technologies in the innovation of traditional ethnic costumes under the protection of traditional techniques and ethnic cultural characteristics. It is precisely for this reason that the current technology integration into clothing design is based on the elements of ethnic clothing or culture, to integrate or innovate.Peng and Krutasaen [9] constructed an ethnic clothing element library system based on artificial intelligence and Internet of Things (IoT) technology, which is used for personalized design of ethnic clothing for customers and can be implemented in mass production.Yu and Cui [10] designed an intelligent ethnic clothing library system based on human-computer interaction and supported by data mining and the Internet of Things (IoT) technology. Internet technical support to design an intelligent ethnic clothing design system, the use of constrained spectral clustering algorithms for customer needs, body and other data processing, the effect of ethnic clothing design to upgrade the role of significant.Han et al [11] used the recognition and generation module of the generative adversarial network model to innovate the design of patterns of traditional Chinese clothing, in terms of the cultural connotations, the sample form, and specifications of the presentation of the aspects are taken into account. Cao and Gao [12] used virtual reality technology to design the national costume of cheongsam type, by parsing the features of cheongsam, extracting the human body features by multiple curve fitting methods, and then extracting the human body features in the virtual scene by cubic polynomial fitting, upgrading the two-dimensional form to three-dimensional presentation, and finally generating the model.Liu [13] mentioned the use of multimedia information collection technology to analyze the Chinese traditional dresses by collecting and analyzing the text, image, video and other information of Han-style embroidery costumes, and the innovative design in multiple perspectives such as color, pattern, and style with the orientation of cultural self-confidence.

3. Numerical computation-based optimization of ethnic dress elements extraction

With the continuous development of society and economy, people's aesthetics of clothing styles have long changed, and now the main popular fashion, rich style styles, colorful and other clothing. However, the slow updating of ethnic dress styles, the fixed color matching and the low production methods have led to the fact that they cannot satisfy the public's beautiful vision of ethnic dress. In this regard, based on the collection of ethnic dress image data set, using the VOLO model, ethnic dress image segmentation and coloring processing, and then realize the extraction of ethnic dress elements, so as to facilitate the fusion design of smart wearable devices and traditional ethnic dress. The specific ethnic dress image segmentation and coloring are as follows:

3.1. Ethnic Costume Image Capture

The digital capture of costumes is called costume photography in film and television, in which the shooting of costume color is an extremely important part of costume digitalization. It reflects the way of thinking of nationalities, shows the existence of nationalities, and can also be used to convey and express information. As for the texture of the photograph, it can be presented with differentiated light intensity and multiple shooting angles. In terms of photography, a high-quality digital camera can produce images with high resolution and high color fidelity.

Throughout the acquisition process, a digital back camera is mainly used for image acquisition, so only this device is described in detail. A digital back camera3 consists of parts such as an image sensor and a processing system, and is also known as a digital back. Compared with ordinary digital cameras, digital backs do not have structures such as lenses and shutters, and need to be attached to other conventional camera bodies before they can be used for shooting. It has a high-resolution CCD sensor, which allows for clear and detailed shooting images. 120 and other format cameras are developed to handle large file sizes well: the uncompressed storage format allows for original picture quality, and the RAW post-processing technology lays the foundation for image processing and restoration.

3.2. Traditional Ethnic Costume Image Segmentation Based on VOLO Modeling

Most current feature encoders are mainly based on Convolutional Neural Networks and Visual Transformer [14]. The former has two major classical network architectures, the residual architecture represented by the network depth and the GoogLeNet family of structures represented by the network width. The latter evolved different combinatorial versions as well as classical models such as the VOLO model. Ethnic dress instance objects are many and the shape scale is not uniform, and the traditional instance segmentation methods are not sufficient in their detail semantic extraction and the boundary semantics between instances are not clear. In order to solve this problem, this section starts from multiple perspectives such as depth, width, feature re-refinement and reduction of semantic information loss of the network architecture, which consists of re-designing the feature extraction coding, reconstructing the jump connections and adopting the multi-scale fusion up-sampling mechanism. Next, the functions and roles of each module are described in detail.

3.2.1. GROT hybrid feature coding. For image segmentation tasks, the residual family of networks and its improved versions have become the preferred choice for most mainstream segmentation architectures to encode the extraction backbone network.The GROT residual network feature extraction backbone network consists of a mixture of three modules: the GRblock, the WGRblock, and the OTblock.

1) Grblock. Assuming that the input of the module is X . H , M denotes the output of the intermediate computational process of the GRblock module, which is shown in Eqs. (1) and (2). F_i

denotes the output feature map of this coding module, and the calculation formula is shown in (3). Namely:

$$H = \left[C_{3\times3}\left(M_p(X)\right), C_{1\times3}\left(C_{1\times1}^{d}(X)\right), C_{3\times1}\left(C_{1\times1}^{d}(X)\right)\right] \tag{1}$$

$$M = \mathrm{Re}LU\left(C_{3\times3}(H) + C_{1\times1}^{d}(X)\right) \tag{2}$$

$$F_i = \mathrm{Re}LU\left(\left(C_{3\times3}(M)\right) + C_{1\times1}^{ic}(H)\right) \tag{3}$$

where M_p and $C_{k\times k}^{d}$ represent the convolutional downsampling operations for maximum pooling and convolutional kernel size $k\times k$, respectively. $C_{1\times1}^{ic}$ represents the residual join mechanism. $C_{X\times Y}$ represents the execution of convolutional kernel size $X\times Y$ convolutional operation. ReLU represents the activation activation function. $[\cdot]$ represents splicing feature fusion by channel direction. It is hereby noted that the meaning of the symbols defined here applies to the whole text and will not be repeated in the sequel.

2) WGRblock. WGRblock integrates the design essence of ResNet and GoogLeNet. The first half of the WGRblock module adopts the GoogLeNet parallel branching method, and the second half adopts the residual connection method.

The residual join module is fed to the fused semantic feature map for further extraction operations. Assuming that the input feature map of the WGRblock module is F_{i-1}, its computational process is shown in Eqs. (4) to (7). F_i is the final output feature map of WGRblock module as shown in Eq. (8). That is:

$$M_1 = C_{1\times1}^{d}\left(F_{i-1}\right) \tag{4}$$

$$M_2 = C_{3\times3}\left(C_{1\times1}^{d}\left(F_{i-1}\right)\right) \tag{5}$$

$$h_i\left(F_{i-1}\right) = \begin{cases} C_{1\times1}^{d}\left(F_{i-1}\right), i=1 \\ C_{1\times1}\left(M_p\left(F_{i-1}\right)\right), i=2 \\ \left[C_{3\times1}\left(M_1\right), C_{1\times3}\left(M_1\right)\right], i=3 \\ \left[C_{1\times3}\left(M_2\right), C_{3\times1}\left(M_2\right)\right], i=4 \end{cases} \tag{6}$$

$$g = \left[h_1, h_2, h_3, h_4\right] \tag{7}$$

$$F_i = \mathrm{Re}LU\left(C_{3\times3}\left(C_{3\times3}(g)\right) + C_{1\times1}^{ic}(g)\right), (1 < i \le 4) \tag{8}$$

3) Otblock. OTblock encoding mainly consists of two parts, Outlooker and Transformer, Outlooker and Transformer self-attention mechanism can be combined to further mine each spatial location semantic information to obtain finer-grained semantic information. Assuming that h_{k-1} is the input of a certain layer in the middle of Outlooker, and s_p^i is the intermediate data Token obtained by downsampling after Outlooker extracts the neighborhood weights, the OTblock coding part is defined by Eqs. (9)~(13). Namely:

$$h_k' = MHOA\left(LN\left(h_{k-1}\right) + h_{k-1}\right) \tag{9}$$

$$h_k = MLP\left(LN\left(h_k'\right)\right) + h_k' \tag{10}$$

$$G_0 = \left[s_p^1 w; s_p^2 w; \cdots; s_p^N w\right] + w_{pos} \tag{11}$$

$$G_l' = MHSA\left(LN\left(G_{l-1}\right)\right) + G_{l-1} \tag{12}$$

$$G_l = MLP\left(LN\left(G_l'\right)\right) + G_l' \tag{13}$$

In Equation (11) $W \in \mathbb{R}^{(p)^2 \times D}$ is the projection of the patch embedding and $W_{pos} \in \mathbb{R}^{N \times D}$ is the positional embedding vector. h_k denotes the output of Outlooker at layer k as shown in Eq. (9), (10). G_l denotes the output of layer l Transformer as shown in Eqs. (12), (13).MHOA, MHSA, MLP, LN stand for Multihead Outlooker Attention, Multihead Self-Attention, Multi-Layer Perceptron, and Layer Normalization Operation, respectively.

3.2.2. Reconstructing jump connections. Jump connections are useful in being able to connect resolution information at different scales, and the use of a convolutional kernel of 1 is intended to enable cross-channel information aggregation to preserve the semantic independence of each spatial location. It also enables the enrichment of shallow feature representations prior to reception at the decoding end. The reconstructed sliding connection definition is shown below:

$$S_i = \begin{cases} F_{3,0}, i = 3 \\ C_{1\times 1}\left(\left[F_{2,0}, Uc_2\left(S_3\right)\right]\right), i = 2 \\ C_{1\times 1}\left(\left[F_{1,0}, Uc_2\left(F_{2,0}\right), Uc_2\left(S_2\right)\right]\right), i = 1 \end{cases} \tag{14}$$

where Uc_x denotes the x -fold transposed upsampled convolution and S_i denotes the output of the reconstructed sliding connection.

3.2.3. Multi-scale upsampling fusion decoder. Two upsampling methods, transposed convolution and bilinear interpolation, are used. The output of the encoding is assumed to be F_4, i.e. $Y_4 = F_4$. The decoding process is defined as shown in Eqs. (15), (16):

$$Y_i = \begin{cases} C_{3\times 3}^2\left[\left(Uc_2\left(Y_4\right)\right), S_i\right], i = 3 \\ C_{3\times 3}^2\left[\left[Ub_2\left(Y_3\right), Uc_4\left(Y_4\right), S_i\right]\right), i = 2 \\ C_{3\times 3}^2\left(\left[Ub_2\left(Y_2\right), Uc_4\left(Y_1\right), Uc_8\left(Y_4\right), S_i\right]\right), i = 1 \end{cases} \tag{15}$$

$$Y_0 = C_{3\times 3}\left(Uc_2\left(Y_1\right)\right) \tag{16}$$

where Ub_x denotes the execution of a bilinear upsampling operation with an upsampling factor of x . $C_{3\times 3}^2$ represents the convolutional kernel size of 3×3 convolution performs 2 operations. Y_i represents the output of the decoding subnetwork. Uc_x is clearly defined above.

3.2.4. Loss function. For the ethnic dress image segmentation task, the loss function and model architecture design are equally important. For the task of segmenting the foreground background of ethnic costumes, the task is reduced to a binary segmentation problem. Therefore, the binary cross entropy loss function is used on this task. The specific formulas are as follows:

$$\mathrm{L}_{ins} = \alpha \cdot \mathrm{L}_{var} + \beta \cdot \mathrm{L}_{dist} + \gamma \cdot \mathrm{L}_{reg} \tag{17}$$

$$\mathrm{L}_{fg} = -\left[y \log \hat{y} + (1-\psi)\log(1-\hat{y})\right] \tag{18}$$

For the instance counting task, the mean-variance loss function is used [15]. It is calculated as shown in Equation (19) and the hybrid loss function for the network model is shown in Equation (20):

$$\mathrm{L}_{mse} = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_t\right)^2 \tag{19}$$

$$\mathrm{L} = \mathrm{L}_{ins} + \mathrm{L}_{mse} + \mathrm{L}_{fg} \tag{20}$$

where L_{ins} denotes the weighted discriminative loss between the predicted instance mask and the real labeled mask as shown in Equation (17). L_{mse} denotes the mean square error loss between the number of predicted instances and the number of real instances in the image. L_{fg} denotes the cross-harmonization loss between the predicted result of binary segmentation and the real labeling in the front and back view of the image.

3.3. *Image coloring of traditional national costumes*

For the task of ethnic clothing grayscale image coloring, some coloring methods have caused great problems in ethnic clothing coloring due to uneven color distribution and large color differences in ethnic clothing. In order to solve this problem, an improved ethnic dress grayscale image coloring method based on GrotUNet fusion instance semantics is proposed. In this section, the design of GRblock and WGRblock modules as above is followed in the encoding part, and some detailed information in it is adjusted. In the decoding part the main and sub decoders are designed. Among them, the main decoder consists of De C2 and De C3, and the secondary decoder consists of De C1. In addition, residual blocks are introduced at the bottom of the network architecture to further mine the feature map. The role of each block is described in detail below.

3.3.1. Encoder design. The GrDbUNet encoder consists of the main Conv, GRblock, GRCblock, and Resblocks blocks. The Conv block contains only one convolutional layer, and the GRblock and GRCblock are derived from the first two blocks in the GROT encoder above.

GRblock maximizes the size of the convolution kernel for the pooling downsampling and then the convolution operation from 3×3 to 1×1. GRCblock adjusts the downsampling convolution kernel size from 1×1 to 2×2 and adds the channel attention module. Assuming input size $X \in R^{2\times H\times W}$, $GRblock$ defines the computational procedure as shown in Eqs. (21) to (29):

$$F_0 = Conv(X) \tag{21}$$

$$h_1 = C_{1\times1}\left(M_p\left(F_i\right)\right) \tag{22}$$

$$h_2 = C_{2\times2}^{d}\left(F_i\right) \tag{23}$$

$$h_{21} = C_{1\times3}\left(h_2\right) \tag{24}$$

$$h_{22} = C_{3\times1}\left(h_2\right) \tag{25}$$

$$g = C_{1\times1}\left(F_0\right) \tag{26}$$

$$m = \left[h_1, h_{21}, h_{22}\right] \tag{27}$$

$$R_1 = Leaky\,\mathrm{Re}\,LU\left(C_{3\times3}(m) + C_{1\times1}^{d}\left(F_i\right)\right) \tag{28}$$

$$F_{i+1} = Leaky\,\mathrm{Re}\,LU\left(C_{3\times3}\left(R_1\right) + C_{1\times1}^{ic}(m)\right) \tag{29}$$

where LeakReLU denotes the activation function. F_{i+1} denotes the output of the GRblock module.GRCblock adds the channel attention mechanism to its middle for measuring the importance of each feature map, thus improving the network's capture of key information.The GRCblock module doubles the size of the downsampling convolution kernel, aiming at retaining more apparel-detailed semantic information. Assuming that the GRCblock input is G_i, the computation process is shown in Eqs. (30) to (36):

$$m_{11} = C_{1\times1}^{d}\left(G_i\right) \tag{30}$$

$$m_2 = C_{1\times1}\left(M_p\left(G_i\right)\right) \tag{31}$$

$$m_3 = C_{2\times2}^{d}\left(G_i\right) \tag{32}$$

$$m_4 = C_{3\times3}\left(C_{2\times2}^{d}\left(G_i\right)\right) \tag{33}$$

$$h = \left[m_{11}, m_2, C_{1\times3}\left(m_3\right), C_{3\times1}\left(m_3\right), C_{1\times3}\left(m_4\right), C_{3\times1}\left(m_4\right)\right] \tag{34}$$

$$S = CA\left(h\right) * h \tag{35}$$

$$G_{i+1} = \mathrm{Re}\,sblock\left(S\right) \tag{36}$$

G_{i+1} denotes the final output of the GRCblock module, where $\mathrm{Re}\,sblock\left(\cdot\right)$ denotes the residual block, and the rest of the symbols are defined as above.GRCblock uses many parallel branching substructures, which are designed to fully exploit the semantic information of the spatial location of the grayscale image, and increase the nonlinear representation. At the same time, the parallel branching structure facilitates the full utilization of GPU arithmetic.

3.3.2. Decoder Design. The decoding side is viewed from the top down, assuming that h_{i+1} is the output from the decoding subnetwork in the next layer and S_i is the connection passed from the corresponding coding side in the current layer. DeC1 is defined as shown in Eq. (37):

$$h_i = C_{3\times3}\left(\left[S_i, h_{i+1}\right]\right) \tag{37}$$

where D_i refers to the current layer of semantic parsing subnetwork output of the subencoder, DeC1 consists mainly of splicing and one convolutional layer. The main decoder consists of two modules, DeC2 and DeC3, where DeC3 is used for the first two modules of the decoder input, and DeC2 is used for the decoding of the shallow feature map. The assumptions of the two are similar to those of DeC1, and DeC2 has only one more convolutional layer than the DeC1 module, achieving significantly different results. One more convolutional layer is more sufficient for the cross-channel interaction of spliced fused feature maps, and the DeC3 module adds a channel attention layer on top of DeC2. CA represents the calculation of the channel attention weights of the fused feature maps after fusion of S_i and D_{i+1}, and assigns the weights to each feature map. The existence of CAttn design at the decoding end is very necessary, which can make the network pay attention to the feature maps with more critical semantic information and accelerate the decoding speed. Namely:

$$d_i = C_{3\times3}\left(C_{3\times3}\left(\left[S_i, d_{i+1}\right]\right)\right) \tag{38}$$

$$D_i = C_{3\times3}\left(C_{3\times3}\left(CA\left(\left[\left[S_i, D_{i+1}\right]\right]\right)\right)\right) \tag{39}$$

4. Innovative Design of Ethnic Clothing Combined with Intelligent Devices

Ethnic dress design refers to an art of designing and matching the above extracted ethnic dress elements (ethnic dress images are taken with the help of equipment, and after image segmentation and coloring, the ethnic dress elements that can be used directly are successfully extracted) according to people's needs and aesthetic concepts. There are many factors to be considered in the design of national costumes, such as the shape of the human body, the occasion of wearing, the cultural background, etc. At the same time, the design of national costumes also needs to be considered. At the same time, the design of ethnic costumes needs to be constantly innovated to meet people's pursuit of fashion and beauty. There is a close connection between wearable devices and ethnic costume design. On the one hand, wearable devices can be used as an extension of clothing, bringing new ideas to ethnic costume design. For example, the elements of national costumes can realize a more intelligent and personalized wearing experience by cooperating with wearable devices. On the other hand, ethnic costume elements can also provide more comfortable and beautiful design solutions for wearable devices to improve the user experience.

4.1. Classification and Development Trends of Smart Wearable Devices

4.1.1. Classification of Smart Wearable Devices. Wearable device is a kind of intelligent device that can be worn on the human body to realize various functions. According to different application scenarios and functions, wearable devices can be categorized into various types [16]. For example, smart watches, smart bracelets, smart glasses, smart clothing and so on. All of these devices have different characteristics and functions, which can meet various needs in people's daily life.

4.1.2. Development trend of smart wearable devices. As technology continues to progress, the wearable device industry is also evolving. In the future, wearable devices will develop in the direction of more intelligent, diversified and comfortable. For example, by combining artificial intelligence technology, wearable devices can realize more intelligent body monitoring, health management and other functions. By linking with other smart devices, wearable devices can realize more diversified application scenarios. By adopting more comfortable and fashionable designs, wearable devices can be closer to people's lives.

4.2. Wearable devices and ethnic clothing fusion innovation design

4.2.1. The concept of integrated design and its necessity. Fusion design is a cross-disciplinary design approach that combines elements and concepts of ethnic clothing in order to create a completely new design. In the field of wearable devices and ethnic clothing design, fusion design refers to combining the smart functions of wearable devices with ethnic clothing elements in order to realize a more intelligent, comfortable and beautiful wearing experience. It can also bring more creativity and possibilities for ethnic clothing design. Therefore, fusion design is necessary.

4.2.2. Specific implementation methods and technical means for integrated design. In terms of material selection, designers need to understand the characteristics, functions and scope of application of the elements of ethnic costumes in order to choose the most suitable materials for production. Designers need to master the relevant production processes and technical means so that they can transform their designs into actual products or works. The use of these methods and technical means can help designers realize the most ideal fusion of wearable devices and ethnic clothing design.

4.3. Garment design based on numerical computation optimization

The fusion design of smart wearable devices and traditional ethnic clothing is a social issue that has attracted much attention. Setting constraints from the user's experience feeling, we establish an optimization model for the fusion design of smart wearable devices and traditional ethnic clothing, calculate the optimal solution of the optimization function through the Drosophila algorithm, and put forward a reasonable design suggestion for the design of the clothing based on the results of the calculation.

4.3.1. Constraints. Firstly, the VOLO model is used to extract the traditional national costume design elements, then the wearable device and traditional national costume design elements are used as the constraints guide, and the information and the design knowledge sources existing in the mind are utilized to quickly find out the various traditional national costume design elements that satisfy the optimization objectives and complete the design process. The focus of the design is how to solve the fulfillment of each constraint.

In apparel design, the essence of apparel design from different ethnic groups, different historical periods, and different cultural backgrounds is often borrowed, and design inspiration is also drawn from other art forms, and this design thinking is called borrowing. In this way of thinking, designers are usually touched by a prominent feature of the borrowed source, which they then wish to introduce into wearable devices. For example, the once-popular Tibetan-style clothing design draws on the ornaments, colors, styles and other features of Tibetan clothing, and then incorporates them into wearable devices after changing them.

Suppose that in the designer's mind there is C_n source of reference, and in each source there are T_i characteristics worth borrowing, $i \in [1, m]$, C_{new} for the new style that the designer is about to form, including p_i elements of the traditional national costume design, and for the elements of the traditional national costume design p_i, there are:

$$p_i = g\left(C_1, T_{pi}\right) \wedge g\left(C_2, T_{pi}\right) \ldots \wedge g\left(C_n, T_{pi}\right) \tag{40}$$

$g\left(C_i, T_{pi}\right)$ indicates that the characteristics of element p_i are extracted from C_i the design elements of traditional national costume T_{pi}, so that the whole wearable device and traditional national costume fusion style for:

$$C_{new} = p_1 \vee p_2 \vee \ldots \vee p_m \tag{41}$$

Design orientation: Wearing environment: {season [constraint 1], time [constraint 2], occasion [constraint 3], ...}}.

Wearing Object: {Gender [Constraint 1], Age [Constraint 2], Personality [Constraint 3], ... }}.

Wearing Purpose: {Casual [Constraint 1], Work [Constraint 2], Recreation [Constraint 3], Sports [Constraint 4], ...}}.

Clothing Style: {Traditional [Constraint 1], Urban [Constraint 2], Avant-garde [Constraint 3], Ethnic [Constraint 4], ...}.

Inspiration theme: <Inspiration theme framework>.

Style pattern: <Style Design Framework>.

Color pattern: <Color pattern framework>.

fabric selection: <fabric selection framework>.

Clothing accessories: <framework for clothing accessories>.

Given a design requirement T, $T = T_1 \wedge T_2 \wedge \cdots \wedge T_n$, denote T as consisting of T_n constraints and let S_k be the set of initial solutions satisfying $T_i \sim T_k$ constraints, i.e.:

$$S_k = f\left(T_1 \ldots T_k\right), k \prec n \tag{42}$$

Next add constraint T_{k+1} and find a suitable change relation f such that:

$$S_{k+1} = f\left(T_1 \ldots T_{k+1}\right) \tag{43}$$

Repeat until $k+1=n$ to obtain the set of style solutions S_n that satisfy the T_n constraints.

Suppose a series of wearable devices and traditional ethnic elements fusion clothing is to be designed. Under this design objective, the dress wear is analyzed to keep up with fashion as well as to reflect the technological elements of wearable devices. Thus, these elements are broken down into design constraints: T_1 : Professional. T_2 : Fashionable and generous: T_3 : Upscale. T_4 : Comfortable.

In order to satisfy T_1 , first choose a series of professional dress style $\{S_1, S_2, \ldots, S_n\}$ to form solution set S_1 , both $S_1 = f(T_1)$: In order to satisfy T_2 , modify the style modeling in S_1 , keep the main modeling elements that reflect the wearable equipment, and form the style solution set S_2 , both $S_2 = f(T_2)$. In order to satisfy T_3 , choose the high-grade fabrics with excellent craftsmanship and elegant colors to form the garment solution set S_3 : In order to satisfy T_4 , choose the soft and stiff, moisture permeable and breathable wool fabrics to form the garment solution set S_4 , and get the final garment design solution:

$$S_4\{S_1', S_2', \ldots, S_n'\} = f(T), \left(T = T_1 \wedge T_2 \wedge T_3 \wedge T_4\right) \tag{44}$$

4.3.2. Objective function:

1) Distance factor. The first consideration is the degree of looseness and tightness of the fusion design work of the wearable device and the traditional national costume elements on the human body, as far as possible, so that the distance between the target work and the target human body is equal to the distance between the basic costume and the basic human body, and this value is expressed by the summation of the quadratic of the distances between each point of the costume mesh and its nearest neighboring human body mesh, that is:

$$C_{dist} = \frac{\sigma_{dist}}{2} \sum_i \left| dist(X_i) - dist(\bar{X}_i) \right|^2 \tag{45}$$

where σ_{dist} is the clothing body distance factor.

2) Stretch factor. Next, it is desired that the ratio of stretch remains constant when the target piece is dressed on the target human body. Eq. (46) describes that the tensile elastic potential energy is proportional to the square of the ratio of the actual length of the mesh edge to the original length, i.e., this ratio describes the magnitude of the tensile energy. While the distance factor above considers the elasticity of the distance between the garment and the human body, this stretch factor considers the elasticity of the garment's own stretch, which is of the form:

$$C_{stretech} = \frac{\sigma_{stretch}}{2} \sum_{i,j} \left| \frac{\|X_i - X_j\|}{\|P_i - P_j\|} - \frac{\|\bar{X}_i - \bar{X}_j\|}{\|\bar{P}_i - \bar{P}_j\|} \right|^2 \tag{46}$$

where, $\sigma_{stretch}$ is the stretch factor coefficient, i, j are the two endpoints of each edge in the grid, X_i and X_j are the target garment grid point coordinates, P_i and P_j are the target artwork grid point coordinates, $\bar{X}_i$ and $\bar{X}_j$ are the base garment grid point coordinates, and $\bar{P}_i$ and $\bar{P}_j$ are the base grid point coordinates.

3) Position Factor. The next step is to keep the relative position of the designed garment pieces consistent with respect to the human body. This relative position is expressed using the relative position of each garment mesh point with respect to its K nearest neighboring triangular human body meshes.

Consider the base human body and the base garment, for each garment mesh point, there exist K triangular face pieces on the human body that are its nearest neighbors. The position of the center of mass of a triangular face piece is given by the average vector of its three vertices, and the relative position of this mesh point with respect to the center of mass of each triangular face piece retains a certain magnitude and orientation; the position factor is to keep this relative position similar.

The factor is written in the following form: the conjectural solution is obtained by adding the target body to the cluster of relative vectors of the base garment over the base body, i.e:

$$X^{guess} = \Phi + \left(\bar{X} - \bar{\Phi}\right) \tag{47}$$

Because the human body model used in this paper has the same number of mesh triangular facets when changing its dimensions and thus constructing different body sizes, but only changes the values of the mesh vertices' coordinates of the human body model, the specific implementation of Eq. (47) is as follows: for each vertex of the base garment $\bar{X}$, search for the triangular facet of its nearest neighbor on the K base human bodies $\bar{\Phi}$, calculate the relative position vectors of the vertices of the garments and the K triangular facets relative position vectors, and the average relative position vector obtained by averaging these vectors is added to the corresponding facets of the new target human body, i.e., the guessed initial solution of the optimization process of the objective function X^{guess} is obtained, which can also be written in the form of the position factor:

$$C_{position} = \frac{\sigma_{position}}{2}\left\| X_i - X_i^{guess} \right\|^2 \tag{48}$$

4) Smoothness factor. The role of this factor is to ensure that the target design work has the same degree of smoothness as the base garment, similar to the paper sample boundary shape factor, however, since the garment is a three-dimensional mesh, its degree of smoothness can not be just through a simple vector dot product, but should be through the local planar properties. The smoothest case, is the case where the bending potential energy is 0. The smoothness factor can be established through the format of discrete bending potential energy, which can be obtained as the purpose of the smoothness factor is to minimize the total bending potential energy, i.e.

$$C_{smooth} = \frac{\sigma_{smooth}}{2}\sum_{\varepsilon_0}\left(\left\|K_0 X\right\| - c\left\|K_0 \bar{X}\right\|\right)^2 \tag{49}$$

where σ_{smooth} is the smooth factor coefficient, where K_0 and c are the values characterizing the concavity and convexity properties of both. Consider two triangles sharing a hinge side in discrete energy, when the angles between two triangles are equal but opposite to each other, the hinge side two triangles have the same angle and each angle within the triangle is the same, so the value of $\left\|K_0 X\right\|$ is the same, but C_{smooth} should not be 0, so the coefficient c is used to characterize the control over the concavity and convexity properties. I.e:

$$c = \frac{\left(K_0 X \cdot n\right)\left(K_0 \bar{X} \cdot \bar{n}\right)}{\left|\left(K_0 X \cdot n\right)\left(K_0 \bar{X} \cdot \bar{n}\right)\right|} \tag{50}$$

where n and $\bar{n}$ are the average normal vectors of two neighboring triangular facets of the target design piece and the base garment, respectively.

5) Numerical calculation optimization process. Summing up all the factors above, the optimization objective function is obtained in the form of:

$$f = C_{dist} + C_{stretch} + C_{position} + C_{smooth} \tag{51}$$

Its design variable is $\Psi = P^{2b}$, the $2b$ coordinate components of the boundary. This objective function includes four factors related to clothing, which completely describes how well the target design piece reduces the basic clothing in terms of both fit and design style.

4.3.3. Drosophila Optimization Solution Algorithm. Combining the above constraints, it is proposed to adopt the Drosophila optimization solution algorithm to solve the above objective function computationally. It realizes the modularization of the fusion design of wearable devices and ethnic costumes, improves the efficiency of the fusion design of wearable devices and ethnic costumes, and avoids the repetition of the tedious process of original modeling of clothing parts. The Fruit Fly Optimization Algorithm (FOA) is a biological optimization seeking algorithm inspired by the foraging behavior of fruit flies [17]. Its algorithm flow is as follows:

1) Set the parameters of the FOA algorithm: the Drosophila population size Popsize and the maximum number of iterations Iteration, X_begin, Y_begin means randomly initialize the Drosophila population position:

2) Calculate the randomized direction and distance of Drosophila individual optimization search by Eqs. (52) and (53):

$$x_i = X\_begin + Value \times rand(\ ) \tag{52}$$

$$y_i = Y\_begin + Value \times rand(\ ) \tag{53}$$

where $Value$ denotes the search distance of the Drosophila: x_i and y_i denote the position of the Drosophila individual at the next moment, respectively.

3) The distance between the fruit fly individual and the origin is calculated by Equation (54) d_i, while the flavor concentration of the fruit fly individual is later calculated by Equation (55) s_i:

$$d_i = \sqrt{x_i^2 + y_i^2} \tag{54}$$

$$s_i = \frac{1}{d_i} \tag{55}$$

4) Substitute the flavor concentration s_i into the flavor concentration decision function as in Eq. (56) to calculate the individual fruit fly flavor concentration at the current location:

$$Smell_i = Function(s_i) \tag{56}$$

5) Find the best flavor concentration value in the Drosophila population indicated by $Smell_b$ and the best position indicated by x_b and y_b.

6) Keep and record the best position of the fruit flies and the best flavor concentration, the best flavor concentration $Smellbest = Smell_b$, the initial position of the fruit flies $X\_begin = x_b$, $Y\_begin = y_b$, while the fruit fly population searches for the current best position.

7) Enter the iterative search for the best, repeat the iterative steps 2) to 5), while determining whether the flavor concentration is better than the previous iteration flavor concentration. If it is valid, go to step 6).

5. Discussion on the innovative design of national costumes

5.1. Evaluation of the extraction effect of national costume elements

5.1.1. Evaluation of image segmentation effects:

1) Experimental environment. The experimental environment in this chapter is built based on the deep learning framework PyTorch combined with Python programming language. The configuration of the computer is as follows: the operating system is ubuntu17.00, the system memory is 8GB, the CPU is Intel Core i7-7700K @4.6GHz, the GPU is NVIDIA GeForce GTX 4080, and the graphic memory is 16G. The experiment is conducted with Adam optimizer for network optimization, and the initial

learning rate of the network is set to 0.0001. The batch size of the model is 3, the batch size of the rest of the model is 1, and the number of iterations for model training is 10.

2) Evaluation Metrics. In this chapter, in order to effectively evaluate the proposed model, five evaluation metrics are introduced, which are Dice coefficient, IoU, precision rate, recall rate, and accuracy, so as to realize the real evaluation of objective experiments. In the image segmentation task, the segmented samples can be categorized into four classes, and the true positive (TP) represents the positive samples that are classified correctly. True Negative (TN) represents negative samples that are categorized correctly. False positives (FP) represent negative samples that are misclassified as positive samples. False Negative (FN) represents a positive sample that was misclassified as a negative sample.The formulas for the five evaluation indicators are as follows:

$$Dice = \frac{2 \cdot TP}{2 \cdot TP + FN + FP} \tag{57}$$

$$IoU = \frac{TP}{FN + FP + TP} \tag{58}$$

$$\Pr ecision = \frac{TP}{TP + FP} \tag{59}$$

$$\mathrm{Re}\, call = \frac{TP}{TP + FN} \tag{60}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{61}$$

3) Comparison of the segmentation results of different loss functions for the Miao ethnic dress pattern. In order to verify the effectiveness of the loss function introduced in this chapter for the segmentation of ethnic dress images, the BCE loss function, Lovász-hinge loss function, and the loss function in this paper were used to conduct performance comparison experiments, and at the same time, in order to avoid the impact of the model proposed in this chapter on the experimental results, the comparison experiments were conducted with the VOLO model, and the results of the segmentation performance comparison under the different loss functions are shown in Fig. 1. The results of the segmentation performance comparison under different loss functions are shown in Fig. 1. It can be seen that under the VOLO model, only the loss function is replaced to ensure that the other parameters of the experiment are consistent, it can be seen that the indicators of the loss function in this paper (0.8942, 0.8837, 0.9241, 0.9563, 0.9729) are better than the other two loss functions, and there is a large improvement. Aiming at the characteristics of ethnic dress images, the loss function in this paper can be effectively applied to ethnic dress image segmentation.

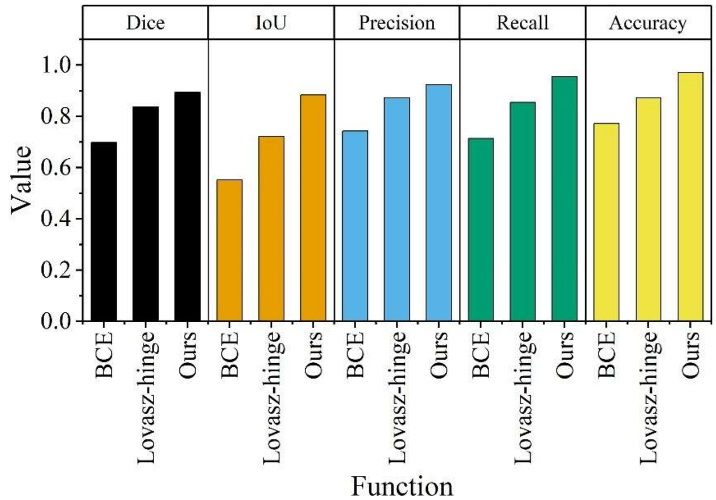


Fig. 1. Segmentation performance under different loss functions

4) Comparison of the segmentation performance of different models for ethnic dress images. In this chapter, several classical mainstream segmentation models are selected to be compared with the model proposed in this paper, and the results of the segmentation performance comparison of different models for ethnic dress images are shown in Figure 2. The model proposed in this paper is better than the other models in terms of segmentation indexes, and the values of its indexes are 90.69%, 83.18%, 90.09, 92.18% and 91.08%. Compared with the benchmark model U-Net model, it improves 6.89%, 11.14%, 2.98%, 6.68%, and 3.86% in the metrics of Dice coefficient, IoU, Precision, Recall, and Accuracy, respectively, so the experimental results from both subjective and objective aspects show that the model proposed in this chapter is better than the rest of the four models. The extraction of elemental content of the Miao dress pattern is realized by segmenting the pattern, and a database of ethnic dress elements can be constructed in this way, thus providing research basis support for the fusion design of smart wearable devices and ethnic dresses.

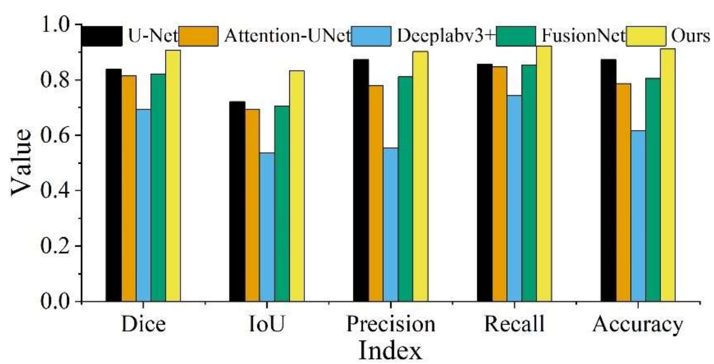


Fig. 2. Comparison of segmentation performance of different models

5.1.2. Evaluation of image coloring effects:

1) Evaluation Metrics. In terms of performance evaluation, the coloring performance of the model is measured by calculating the PSNR peak signal-to-noise ratio, SSIM structural similarity and LPIPS perceptual similarity between the generated image and the real image in RGB space, and all three quantify the distance between the generated image and the real image in RGB space. Namely:

$$MSE = \frac{1}{h \times w} \sum_{i=0}^{h-1} \sum_{j=0}^{w-1} \left[I(i,j) - G(i,j) \right] \tag{62}$$

$$PSNR = 20 \times \log_{10}\left(\frac{MAX_1}{\sqrt{MSE}}\right) \tag{63}$$

$$l(I,G) = \frac{2\mu_I\mu_G + c_1}{\mu_I^2 + \mu_G^2 + c_1} \tag{64}$$

$$c(I,G) = \frac{2\sigma_1\sigma_G + c_2}{\sigma_I^2 + \sigma_G^2 + c_2} \tag{65}$$

$$s(I,G) = \frac{\sigma_{IG} + c_3}{\sigma_I\sigma_G + c_3} \tag{66}$$

$$SSIM(I,G) = l(I,G) \times c(I,G) \times s(I,G) \tag{67}$$

where, I and G denote the coloring image of size $h \times w$ and the real image respectively, MAX_1 denotes the maximum pixel value in units of dB, μ_I and μ_G are the mean of I、G respectively, σ_I^2 and σ_G^2 are the variances of I and G respectively, σ_{IG} is the covariance of I and G, $c_1 = (k_1L)^2$, $c_2 = (k_2L)^2$ and c_3 are generally taken as the generality of c_2, and L i.e., MAX_1, k_1 and k_2 above are 0.01 and 0.03 respectively.

2) Comparative analysis of training capacity and time performance. In order to confirm the training loss effect and time performance of the model in this paper, different model structures are used for comparison. As shown in Table 1 and Table 2, a single autoencoder structure model, a model containing residual network structure and a model containing UNet structure are designed in this paper. In order to ensure the fairness and reasonableness of the experiments, the same loss function, learning rate and training batch are used for each model. In Table 1, the loss function of this paper's model decreases the fastest (from 0.2994 to 0.1030), indicating that it has good and fast learning ability. From Table 2, it can be seen that the model in this paper has good time performance. It saves a lot of time compared to the autoencoder method and the residual structure method. Although the model in this paper is a little slower than the method using UNet, the model in this paper can get better coloring results than the method using UNet.

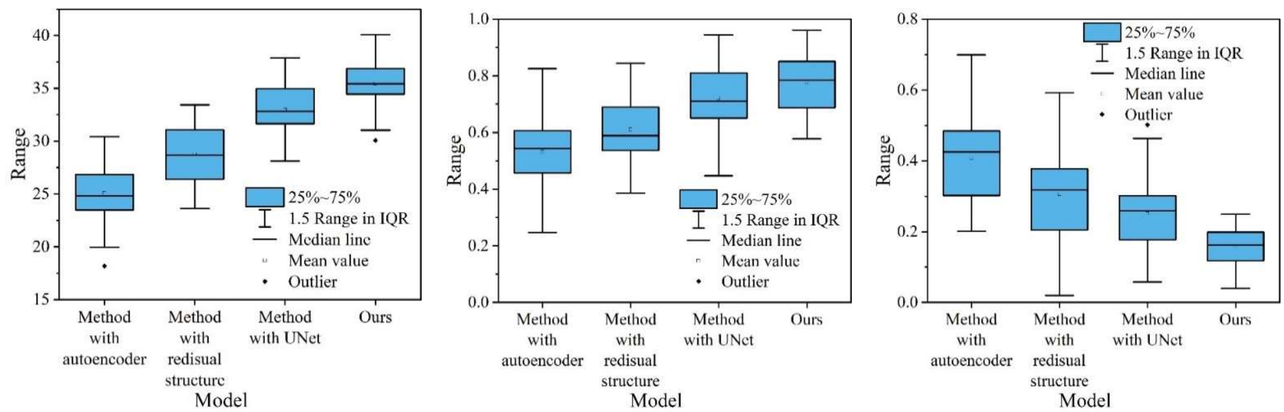
Table 1. Comparison of training ability

N	Method with autoencoder	Method with redisual structure	Method with UNet	Ours	N	Method with autoencoder	Method with redisual structure	Method with UNet	Ours
1	0.9185	0.7015	0.4488	0.2994	26	0.1462	0.1757	0.1230	0.1066
2	0.7789	0.6202	0.3828	0.2129	27	0.1435	0.1724	0.1218	0.1065
3	0.6517	0.5389	0.3569	0.1740	28	0.1409	0.1691	0.1205	0.1064
4	0.5481	0.4756	0.3378	0.1533	29	0.1382	0.1659	0.1193	0.1062
5	0.4659	0.4191	0.3186	0.1404	30	0.1355	0.1626	0.1181	0.1061
6	0.3940	0.3819	0.3019	0.1306	31	0.1329	0.1593	0.1168	0.1060
7	0.3421	0.3448	0.2863	0.1270	32	0.1313	0.1563	0.1156	0.1059
8	0.2916	0.3216	0.2707	0.1233	33	0.1304	0.1536	0.1144	0.1058
9	0.2674	0.3017	0.2552	0.1196	34	0.1295	0.1508	0.1136	0.1057
10	0.2432	0.2817	0.2396	0.1160	35	0.1286	0.1481	0.1128	0.1056
11	0.2210	0.2679	0.2282	0.1140	36	0.1276	0.1453	0.1120	0.1055
12	0.2124	0.2599	0.2167	0.1121	37	0.1267	0.1426	0.1112	0.1054
13	0.2037	0.2520	0.2053	0.1101	38	0.1258	0.1398	0.1104	0.1053
14	0.1950	0.2440	0.1938	0.1082	39	0.1249	0.1371	0.1096	0.1052
15	0.1864	0.2361	0.1827	0.1077	40	0.1240	0.1343	0.1088	0.1051
16	0.1782	0.2281	0.1755	0.1076	41	0.1231	0.1316	0.1081	0.1050
17	0.1748	0.2202	0.1682	0.1075	42	0.1221	0.1289	0.1073	0.1049
18	0.1713	0.2139	0.1610	0.1074	43	0.1212	0.1261	0.1065	0.1048
19	0.1678	0.2080	0.1538	0.1073	44	0.1207	0.1234	0.1057	0.1046
20	0.1644	0.2021	0.1465	0.1072	45	0.1204	0.1206	0.1049	0.1043
21	0.1609	0.1962	0.1410	0.1071	46	0.1202	0.1190	0.1047	0.1041
22	0.1574	0.1903	0.1370	0.1070	47	0.1199	0.1186	0.1047	0.1038
23	0.1541	0.1855	0.1330	0.1069	48	0.1197	0.1182	0.1047	0.1035
24	0.1515	0.1822	0.1289	0.1068	49	0.1194	0.1178	0.1047	0.1033
25	0.1488	0.1789	0.1249	0.1067	50	0.1191	0.1174	0.1047	0.1030

Table 2. Time performance comparison

N	Method with autoencoder/s	Method with redisual structure/s	Method with UNet/s	Ours/s	N	Method with autoencoder/s	Method with redisual structure/s	Method with UNet/s	Ours/s
1	97	94	88	89	26	295	279	268	268
2	104	102	95	96	27	303	287	275	275
3	112	109	102	103	28	310	294	282	282
4	120	117	109	110	29	318	302	289	289
5	128	124	116	118	30	325	309	296	296
6	135	132	124	125	31	333	317	302	303
7	143	139	131	132	32	341	324	309	310
8	151	147	138	139	33	348	331	316	318
9	158	155	145	147	34	356	339	323	325
10	166	162	153	154	35	363	346	330	332
11	174	170	160	161	36	371	354	337	339
12	181	177	167	168	37	378	361	344	346
13	189	185	174	176	38	386	369	351	353
14	197	192	181	183	39	395	377	358	361
15	205	200	189	190	40	403	384	366	368
16	213	207	196	197	41	411	392	373	376
17	222	214	203	204	42	420	400	381	384
18	230	221	210	211	43	428	408	388	391
19	238	229	218	218	44	436	416	396	399
20	246	236	225	225	45	445	424	403	407
21	254	243	232	233	46	453	432	411	414
22	263	250	239	240	47	462	439	418	422
23	271	258	246	247	48	470	447	425	429
24	279	265	254	254	49	478	455	433	437
25	287	272	261	261	50	487	463	440	445

3) Comparison of coloring effect of national costumes. The results of the comparison of the coloring effect of ethnic clothing are shown in Fig. 3, where (a)~(c) are PSNR, SSIM, and LPIPS, respectively. Based on the data performance in the figure, all the indexes of this paper's model (35.41±2.11, 0.82±0.12, 0.19±0.04) are more excellent than the other three models, which indicates that after using this paper's model for coloring of ethnic costumes, the gap between the colorized image and the original colorful image is much smaller, which proves that this paper's model has a good application efficacy for extracting the elements of the ethnic costumes.



(a)PSNR (b)SSIM (c)LPIPS

Fig. 3. Results of color effect comparison of ethnic costumes

5.2. The Innovation Effect of Traditional Ethnic Clothing Based on Smart Wearable Devices

5.2.1. Analysis of application examples. In practical applications, in general, the maximum error of the objective function value of the fusion design of intelligent devices and ethnic clothing is 5%, and the clothing orders are shown in Table 3, and the fruit fly optimization solution algorithm is used to optimize the clothing orders in the table, and the values of the four objective factors (the distance factor Y1, the stretching factor Y2, the position factor Y3, and the smoothing factor Y4 mentioned above) are recorded, and the results of optimization of the objective function value are shown in Table 4. Based on the data performance in the table, it can be seen that the values of the four objective factors are 0.233, 0.232, 0.348, and 0.144, respectively. On the basis of the known values of the four objective factors, the objective function value of the fusion design of intelligent devices and ethnic clothing is calculated by using formula (51), which results in an objective function value of 0.957, indicating that after optimization of the Drosophila algorithm, the fusion design work of intelligent devices and ethnic clothing is made more in line with the current user's wearing needs.

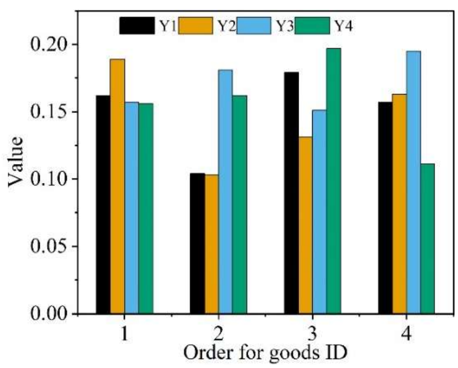
Table 3. Clothing order

Order for goods ID	Color	Size				
		XS	S	M	L	XL
1	Dark blue	316	1068	1158	611	167
	Black	47	178	239	184	68
3	Yellow	135	169	105	19	0
	Beige	174	239	136	19	0
	Black	174	256	147	38	0
3	Black	406	706	777	457	212
	Hemp Grey	148	345	219	239	47
	Dull red	106	158	107	107	16
	Dark Blue	106	238	325	238	106
4	Black P94	109	246	447	439	306
	Black P95	54	118	219	217	148
	Light green P86	107	208	354	336	226
	Light green P87	107	208	354	336	226
	Dark green P85	79	179	335	329	226

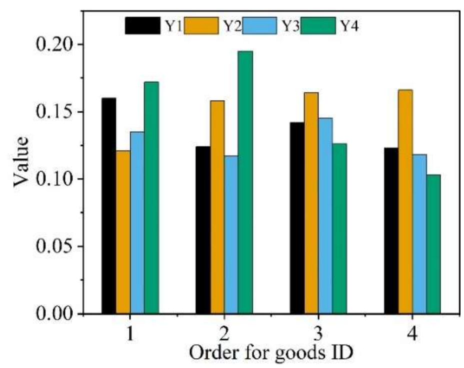
Table 4. Optimize the result of the objective function value

Order for goods ID	Y1	Y2	Y3	Y4
1	0.214	0.213	0.358	0.176
2	0.258	0.236	0.382	0.127
3	0.212	0.227	0.339	0.134
4	0.246	0.252	0.311	0.137
Total	0.233	0.232	0.348	0.144

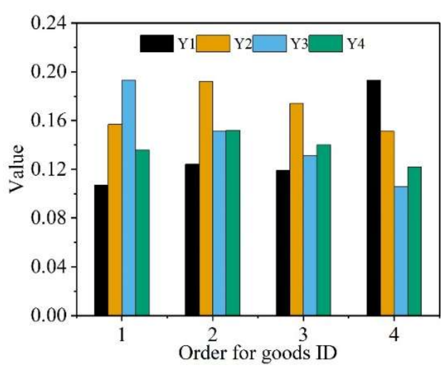
5.2.2. Comparative experimental analysis. In order to evaluate the comprehensive performance of the proposed algorithm more comprehensively, the algorithm in this paper (FAO: Drosophila algorithm) is compared with the existing methods (PSO: Particle Swarm Algorithm, GA: Genetic Algorithm, SA: Simulated Annealing Algorithm), and the results of the comparative experiments are shown in Fig. 4, in which (a) to (d) are PSO, GA, SA, and FAO, respectively, and the results of the comparative experiments are shown in Fig. 4, where (a) to (d) are PSO, GA, SA, and FAO, respectively. Y3, and smooth factor Y4, the four objective factors of PSO, GA, and SA are out of the interval of 0.1~0.2, however, the values of the factors of the fruit fly algorithm are located in the interval of 0.1~0.3, and the four algorithms solve the objective function values of 0.625, 0.567, 0.587, and 0.957, which is better compared to the optimization results of PSO, GA, and SA. It shows that the Drosophila algorithm plays an important role in the process of fusion design of smart devices and ethnic clothing, which can improve the comfort and user experience of the devices, and provide new creativity for the fusion and development of the clothing industry and wearable device industry.



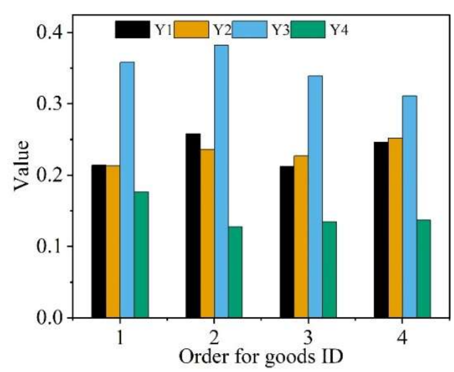
(a)PSO



(b)GA



(c)SA



(d)FAO

Fig. 4. Compare the experimental results

6. Conclusion

In this paper, a digital back camera is used to capture the images of traditional ethnic costumes and save them in the form of datasets. Then its image is segmented and colored using VOLO model to provide material support for the subsequent clothing fusion design. According to the classification and development trend of wearable devices, a specific implementation plan for the fusion design of the two was formulated, in addition to setting constraints, objective functions, and using numerical computation optimization methods to analyze the design works. The objective function values of PSO (Particle Swarm Algorithm), GA (Genetic Algorithm), SA (Simulated Annealing Algorithm), and FAO (Fruit Fly Algorithm) are 0.625, 0.567, 0.587, and 0.957, and the FAO algorithm adopted in this paper performs more prominently compared to PSO, GA, and SA, which indicates that the algorithm plays an optimization role in the fusion design of smart devices and ethnic clothing, making the designed works more suitable for the wearable devices and ethnic clothing. This shows that the algorithm plays an optimization role in the fusion design of smart devices and ethnic clothing, which makes the designed works more suitable for the users' wearing needs and aesthetic standards, and also provides innovative value for the fusion design of the two.

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