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Article

Generative Model-Based Personalized Design of Non-Heritage Cultural and Creative Products and The Path of Remodeling Rural Cultural Resources

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Abstract: This paper proposes a non-heritage cultural and creative generation product design effect image method based on StyleGAN. On this basis, the personalized design of non-heritage cultural and creative products is carried out, and the weights of the parameters are determined by adopting the method of interactive selection with the participation of target customers. The problem that traditional interactive genetic algorithm cannot effectively reduce user fatigue is improved by mutating individuals and genetic operation, and it is applied to multi-function product configuration design. The required initial shapes and inference rules are extracted from past products, and functional constraints are imposed on the product while obtaining a solution that meets the product design requirements. The results show that StyleGAN model is more effective for personalized design of non-heritage cultural and creative products, and its comprehensive satisfaction rate reaches 85.36%. When the number of iterations reaches 85, the fitness value of the non-heritage cultural and creative products generation model is gradually stabilized and finally reaches 1.5686, which shows that the model in this paper can obtain a satisfactory solution before reaching the maximum number of hereditary generations, proving that it is more effective in the derivation of non-heritage cultural and creative products. Finally, through the three forms of "extraction and innovation, reorganization and deformation, transplantation and grafting", the cultural symbols are integrated into the design practice to create a brand of non-heritage cultural and creative products with the characteristics of rural cultural resources.

Keywords: StyleGAN; Genetic Algorithm; Improved Interactive Genetic Algorithm; Non-heritage Cultural and Creative Products

1. Introduction

Non-heritage cultural and creative products are cultural and creative products developed by combining non-heritage elements with modern creative design. These products are usually based on traditional skills, stories or cultural symbols and presented in an innovative way, aiming at preserving and inheriting NRLs while meeting the needs of modern consumers, which is an important carrier of traditional cultural heritage [1-2]. With the booming development of tourism, tourists' interest in and demand for non-heritage cultural and creative works with local characteristics and cultural heritage are rapidly increasing. Special research shows that the proportion of consumers buying local cultural and creative products in cultural consumption expenditure has reached 55%, 75% of cultural enterprises believe that the cultural consumption market will focus on cultural products such as cultural creations and non-heritage, and governments at all levels have gradually recognized the value and market potential of non-heritage culture and have introduced relevant policies to promote its protection and development [3-6].

However, the current market of non-heritage cultural and creative product design style, functionality and lack of differentiation. The main reason is that the development cost of cultural and creative products is high, the design cycle is long, and enterprises ignore the cultural depth of the products in order to pursue short-term market benefits [7]. Now there are many cultural and creative products on the market in the "wholesale" mode of production, the ornamentation, graphics, color, direct application, did not take into account whether the design is in line with the significance of the culture itself, so that the creation of cultural and creative products are detached from the original cultural connotation, lost contact with traditional culture, these products have artistic effect, but lack of recognition. Although these products have artistic effects, they lack recognition and are difficult to stand out in the fierce market competition [8-11]. Moreover, due to the increasingly prominent demand for consumer personalization, consumers have also added personalized demand for cultural and creative products on the basis of quality, and all these factors have urged the non-heritage cultural and creative products to personalized design [12]. Most of the non-heritage cultural and creative products originate from rural cultural resources and possess local rural cultural characteristics. However, in the modernization process continues to promote, the deepening of urbanization, the traditional rural culture is facing a growing decline in the current situation, countless intangible cultural heritage, traditional customs and folk skills and other traditional rural cultural resources are gradually disappearing [13-14]. The destruction of rural cultural resources is more than enough but the reconstruction is not enough, and the alienation of traditional ethics and morality in rural society is serious, which gradually disappears the spirit of rural culture and impacts the stability and order of rural society [15]. The ideals of the family and the country, the ritual order, and the moral beliefs in the traditional rural culture play an important role in uniting people's hearts, and simplifying the people's morals, etc. The importance of traditional rural cultural inheritance is self-evident.

With the progress of global digitization, generative models are emerging in product design and cultural preservation. Through generative artificial intelligence, not only can efficient cultural and creative product design be realized, but also new patterns with different styles and patterns can be designed based on traditional patterns or motifs [16-17]. Moreover, the generative model can learn a variety of traditional crafts, patterns and other cultural resources, and will retain the cultural genes of the resources, whose purity is more than 90%, and will not affect their subsequent cultural and creative product design [18]. At the same time, it solves the problem of homogenization of cultural and creative products, and also provides a path for remodeling rural cultural resources.

In this paper, using image deformation technology, StyleGAN method that can quickly generate product effect images is proposed, and the method is used to generate real product effect images of non-heritage cultural and creative products after personalized design. Afterwards, in order to optimize the design effect of the product, the product shape is encoded first, and then the parameter values of all layers of morphological encoding are gradually solved by interactive genetic algorithm. After that, the improved interactive algorithm is used to divide the individuals into different genetic units, and the multi-user collaborative configuration is accomplished through users with similar preferences to design satisfactory works, and the design effect of the improved method in non-heritage cultural and creative products is analyzed. Finally, the method of transforming design elements for rural cultural resources is proposed.

2. StyleGAN-Based Product Design Method and Effects

2.1. The Method of Personalized Design Effect of Non-Heritage Cultural and Creative Products

2.1.1. Design Fundamentals

(1) GAN

The GAN model [19] contains a generator, discriminator network. The generator is designed to generate images whose authenticity cannot be determined by the discriminator, and the discriminator is designed to distinguish the authenticity of the incoming images. The generator and the discriminator play with each other, during the training process, the discriminator and the generator will each update the parameters to minimize the loss, and through this continuous iterative optimization, the state of Nash equilibrium is finally reached.The objective function of GAN is defined as follows:

$$\min_G \max_D V(G,D) = E_{X-P_{duu(x)}}[\lg D(x)] + E_{z-P_{z(z)}} \lg\{1-D[G(z)]\} \tag{1}$$

where: X denotes a random sample from the distribution of real pictures $P_{data(x)}$, $y = (y_s, y_b)$ denotes a random vector of samples from a normal distribution, $D(x)$ denotes the probability of categorizing a true sample as true, and $1 - D[G(z)]$ denotes the probability of categorizing a false sample as false.

(2) StyleGAN

StyleGAN [20] is a derivative network of GAN, which mainly improves the network architecture of the generator, aiming to reduce feature entanglement and improve the ability of style control.StyleGAN changes the generator to be composed of two parts: the mapping network and the synthesized network, which have the following effects, respectively:

First, in order to reduce feature entanglement, the mapping network is designed to consist of eight fully connected layers that can encode the input vectors into intermediate vectors, which are then transformed into feature codes (style control vectors) $y = (y_s, y_b)$ by a learnable affine transformation to each convolutional layer in the synthesized network with Adaptive Instance Normalization (AdaIN) operations, which are defined as follows:

$$AdaIN(X_i, y) = y_{s,i} \frac{X_i - \mu(X_i)}{\sigma(X_i)} + y_{b,i} \quad (2)$$

where: X_i denotes each feature map, and $\mu(X_i), \sigma(X_i)$ represents the mean and standard deviation of the feature map, respectively.

Second, to improve the style control and training efficiency, the structure of the synthetic network is borrowed from the ProGAN model. Firstly, it learns the basic features that can be shown even in low resolution images, and uses the learned basic features as the basic part of creating images, and as the resolution increases, the learned details also increase.StyleGAN achieves the purpose of controlling the specific features of the image and improving the efficiency of the model training through the improvement of the generator.

(3) StyleGAN-encoder

StyleGAN is able to generate images with mixed styles by randomly combining the cryptograms of two random images, and because StyleGAN is unsupervised to generate images using two random cryptograms with style mixing, it is not possible to modify the given image style.

(4) Image morphing based on StyleGAN-encoder

StyleGAN-encoder can embed the specified image into the latent space of StyleGAN. Given two more embedded images with their respective latent vectors ω_1 and ω_1 , the transformation is computed by linear interpolation as follows:

$$\omega = \lambda\omega_1 + (1-\lambda)\omega_2, \lambda \in (0,1) \quad (3)$$

The image is then generated using the new encoding ω . The linear difference computation of StyleGANencoder enables different degrees of style blending between the specified two images.

2.1.2. StyleGAN-Based Design Method for Non-Heritage Cultural and Creative Products

(1) Method flow

This paper proposes a method based on Style GAN for generating product design effect images of non-heritage cultural and creative products, which mainly uses Style GAN and StyleGAN- encorder, and proposes an innovative design method based on these two models that is applicable to generating product design effect images of non-heritage cultural and creative products.

For the hand-drawing accuracy error: according to whether the user has a drawing foundation or not, it is divided into a professional group and an amateur group, and different degrees of linear interpolation results are selected to give different degrees of deformation.

For imagery style elements: the non-heritage cultural and creative products drawn by the designer and the selected target style images are used as inputs, both of which are based on the designer's imagery style to complete the selection. Finally, based on StyleGAN-encoder to complete the linear interpolation of the two input images to calculate the results take 1/8 can generate the best program.

(2) Key Technology

Based on StyleGAN non-heritage cultural and creative products to generate product design effect map method, the most critical is the linear interpolation technology of StyleGAN-encoder, to realize the non-heritage cultural and creative products and the target style image of different degrees of style mixing. First, the non-heritage cultural and creative products drawn based on the designer's imagery style and the selected target style image are input into the StyleGAN-encoder at the same time, and then the fusion image of the two is constructed through the linear interpolation computational transformation, and with the different values of λ, the generated fusion effect image of the non-heritage cultural and creative products and the target style is also diversified.

2.2. Network Training and Result Analysis of Non-Heritage Cultural and Creative Product Generation Experiments

The maximum number of training rounds for SketchGAN is set to 5000, the random noise of the input generator is 125 dimensional, and the batch size batchsize is set to 65. The generator and discriminator are trained using the Adam optimizer with an initial learning rate of 0.0001 for both, $\beta 1 = 0.5$, $\beta 2 = 0.999$, and no decay strategy. Adversarial loss balancing factor $\lambda_{adv} = 1$, and gradient penalty balancing factor $\lambda_{gp} = 10$ for the discriminator. The values of λ_{gp} in the interval [6, 10] are tested experimentally for successful training. The discriminator is trained first, and the generator is trained later, with the discriminator trained once every 1 batch and the generator once every 7 batch.

The loss variation results of the discriminator are shown in Fig. 1; the loss variation results of the generator are shown in Fig. 2. From the figure, it can be seen that the loss of the discriminator shows intermittent jump change, indicating that its training process does not appear gradient disappearance, thus providing a guarantee for training effective generators. From the loss function change of the generator in the figure, it is found that the model after about 1800 iterations becomes unstable, the error increases, the pattern collapse phenomenon occurs, and the model design outputs the lack of diversity of the non-heritage cultural and creative products, and the training can be stopped. However, the error of the model trained around the 160th epoch is basically near 5%, and the model stability is good.

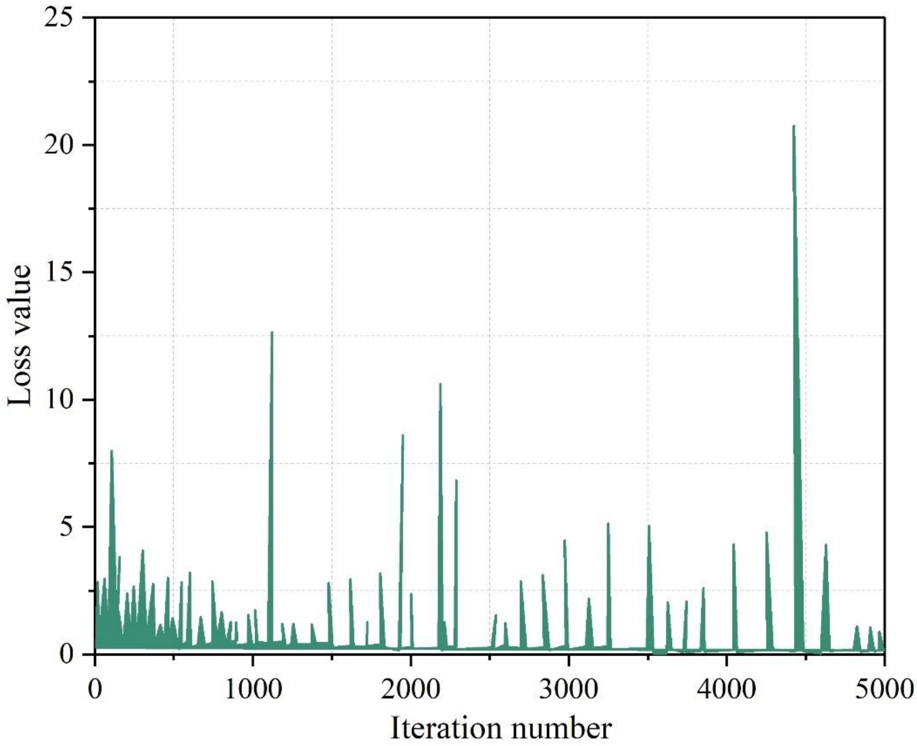


Figure 1. The loss of the discriminator.

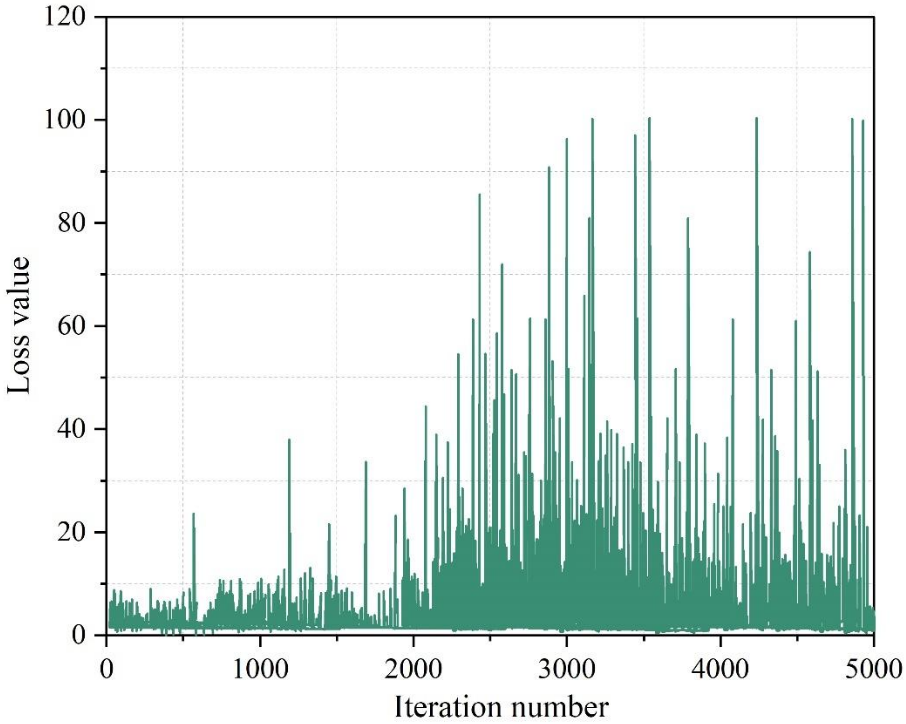


Figure 2. The loss of the generator changes.

2.3. Example Validation

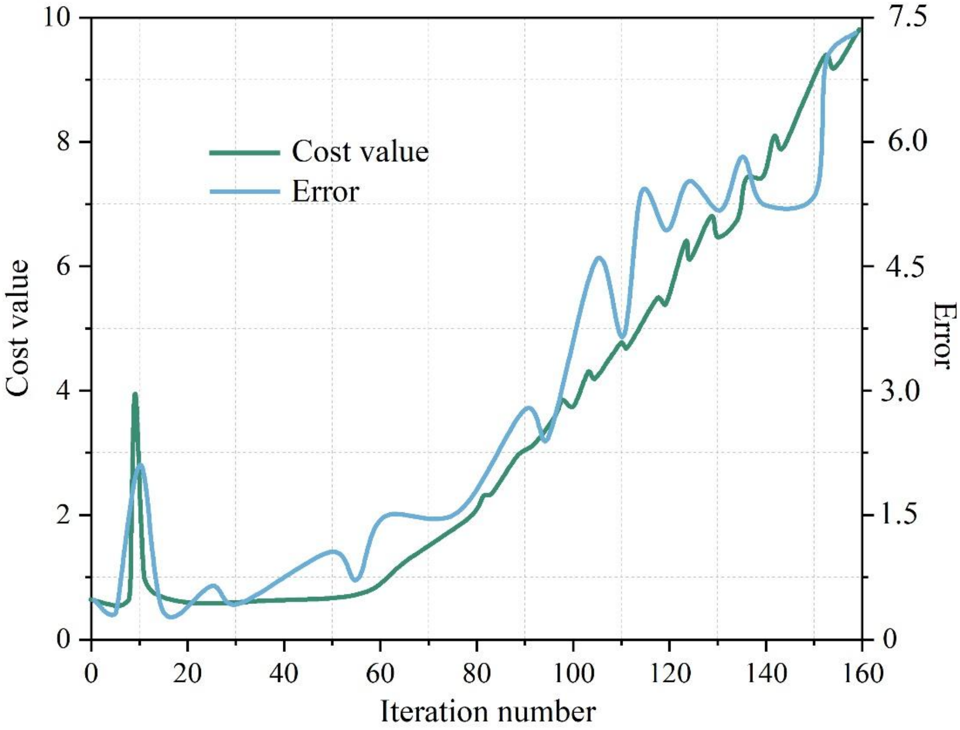
2.3.1. Experimental Data

A dataset is a collection of a set of data, and in the design field, the difficulty of how effective the algorithm is lies in the accumulation of the basic dataset, and less training data often leads to poorer effectiveness and accuracy of the algorithm at a later stage. Taking the styling images of personalized design of non-heritage cultural and creative products as an example, the sample collection is studied on the official website of international non-heritage cultural and creative products, and the database includes 16,523 images, which come from more than 190 different non-heritage cultural and creative products. Through the unified classification of all the non-heritage cultural and creative products in the dataset, two types of sample pictures of non-heritage cultural and creative products with richer resources in the database are finally collected: 8569 pictures of non-heritage skill ontology transformed products, and 7954 pictures of non-heritage element creative derived products. On the other hand, the images of NRH cultural and creative products are crawled by web crawler to increase the sample size.

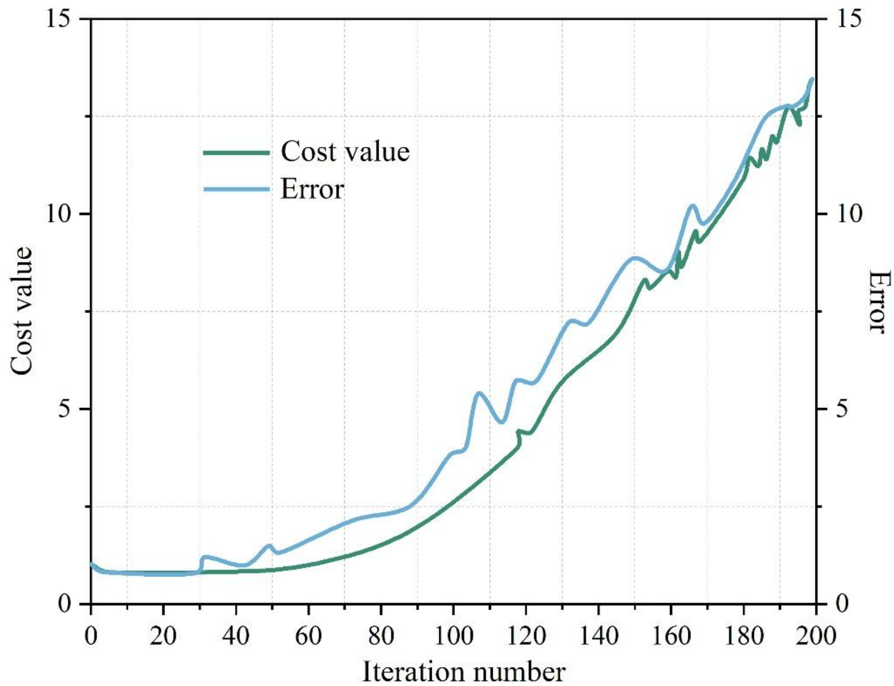
In order to balance the number of datasets of the two types of works, the images obtained from the web crawling method of NRT ontology transformed products and the original dataset of NRT creative derived products were expanded by four traditional data enhancement methods: horizontal flipping, random cropping, random color, and Gaussian noise, respectively. The two types of total images were used as the base data set, and the ratio of the training set to the test set was set to be 4:1 when importing the base data set, and the computer randomly divided the base data set into the training set and the test set in accordance with the ratio, so that the final data set obtained was composed as follows: in the training set and the test set, the number of transformed products of the NRL art ontology were 27420 and 6856, respectively; the number of product pictures of the creative derivative of NRL elements were 25452 and 25452, respectively. The product images are 25452 and 6364 respectively.

2.3.2. Analysis of the Performance Effect of the Model on the Design of the Products

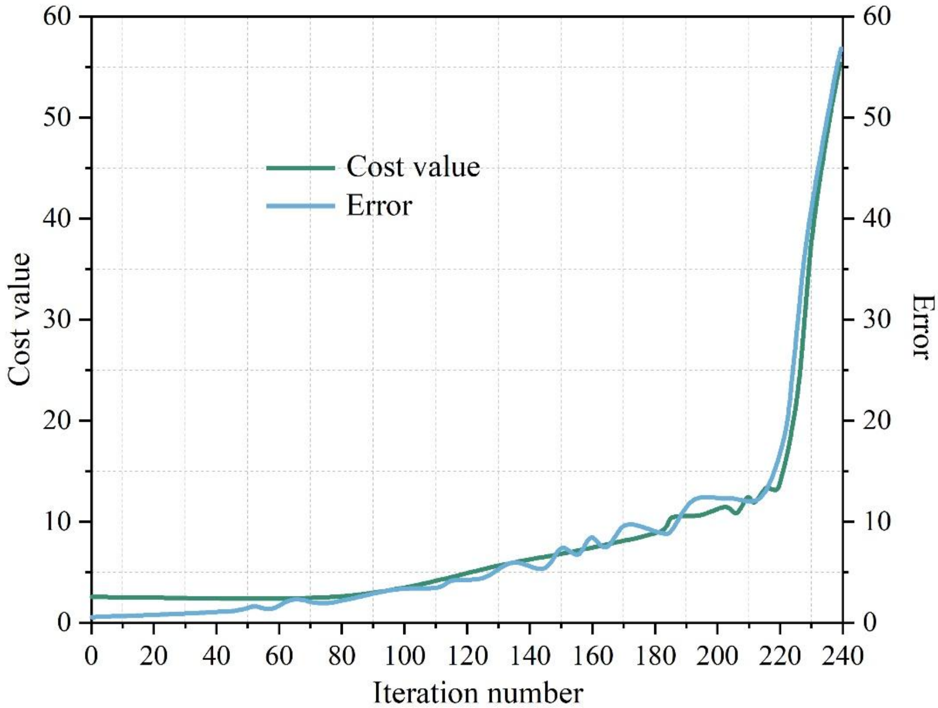
The total number of iterations for different experiments is shown in Fig. 3, where (a)~(c) represent 160, 200 and 240 iterations, respectively. After many experiments, it has been proved that the number of iterations is around 216 times when the generation value of the learning curve and the training error value will be rapidly increased, resulting in the generation of a large number of erroneous results, so the number of iterations chosen for this experiment is 190 times. From the output results of the model, it can be seen that the generated images become clearer and clearer with the increase of the number of iterations, indicating that the algorithm in this paper obtains more information about the images of the non-heritage cultural and creative products from the training dataset, which improves the ability to generate images.



(a) The total iteration of the experiment was 160 times



(b) The total iteration of the experiment was 200 times



(c) The total iteration of the experiment was 240 times

Figure 3. Total iterations of different experiments.

2.3.3. Validity Test of Model Performance

The non-heritage technology ontology transformed products, non-heritage elements creative derivative products are divided into 2 groups, and each group is screened 3 programs from the pictures generated by the model generator of this paper, and compared with the design programs designed by the 3 experts of the 2 groups respectively. The 5 design experts give 4 decision criteria evaluation scores for each design scheme, and according to the weights of the 4 decision criteria, 3 groups of design comprehensive satisfaction rate curves can be obtained, and the higher the satisfaction rate is, the better the performance of the tested model is. The higher the satisfaction rate, the higher the performance of the tested model. The comprehensive design satisfaction rate curve can be used to judge how good or bad the model generates pictures, and the comprehensive design satisfaction rate curve can be obtained by connecting the points.

The comprehensive satisfaction rate of the design of the transformed product of the ontology of non-heritage skills is shown in Figure 4. As can be seen from the figure, with the increase in the number of iterations, the satisfaction rate of the pictures generated by this paper's design model rises gradually; when the number of iterations is around 109, the design comprehensive satisfaction rate curve tends to stabilize; when the total number of iterations reaches 190, the satisfaction rate of the pictures generated by the three this paper's design model is 84.25%, 79.16%, 71.72%, respectively, except for the second expert design proposal, which is 76.22%. The satisfaction rate of the other two design schemes is 87.58%, 73.11% and slightly higher than the design scheme of this paper, except the satisfaction rate of the 2nd expert design scheme is 76.22% and slightly lower than the design scheme of this paper.

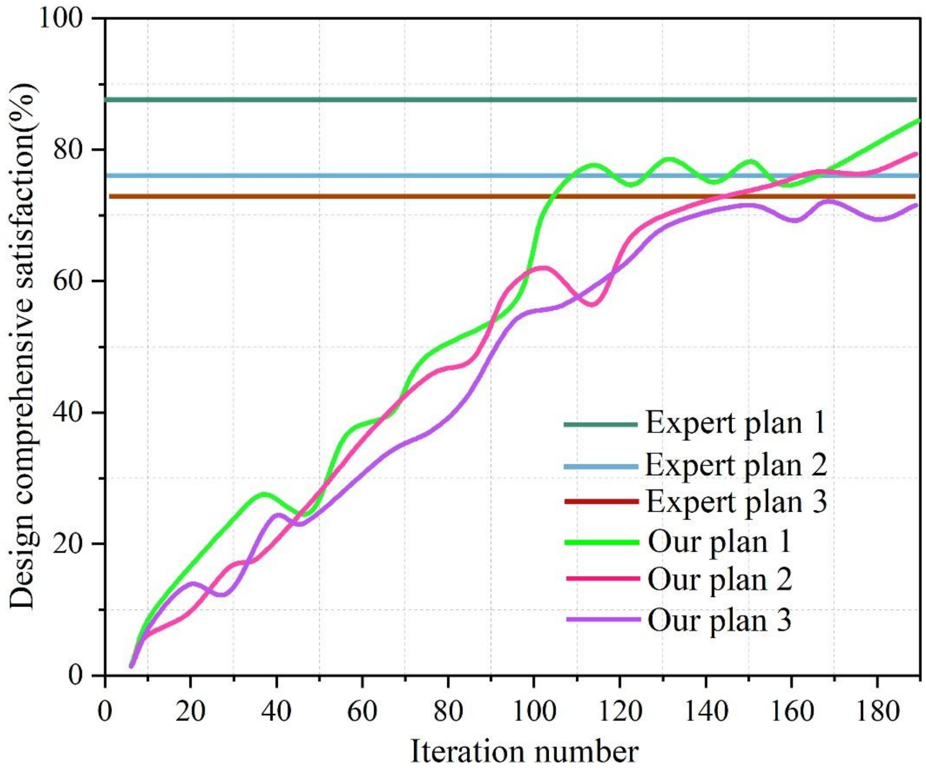


Figure 4. Non-legacy product design comprehensive satisfaction rate.

The results of the comparison of the comprehensive satisfaction rate of the styling design of the creative derivative-type products with non-heritage elements are shown in Figure 5. When the number of iterations is 190 times, the satisfaction rates of the 3 schemes are 77.40%, 73.50% and 70.56% respectively, and the highest values of the satisfaction rates of the 3 expert design schemes are 80.91%, 75.06% and 66.46% respectively. The comparison shows that the satisfaction rate of the design model in this paper is slightly lower than the satisfaction rate of the expert design scheme in all 3 schemes.

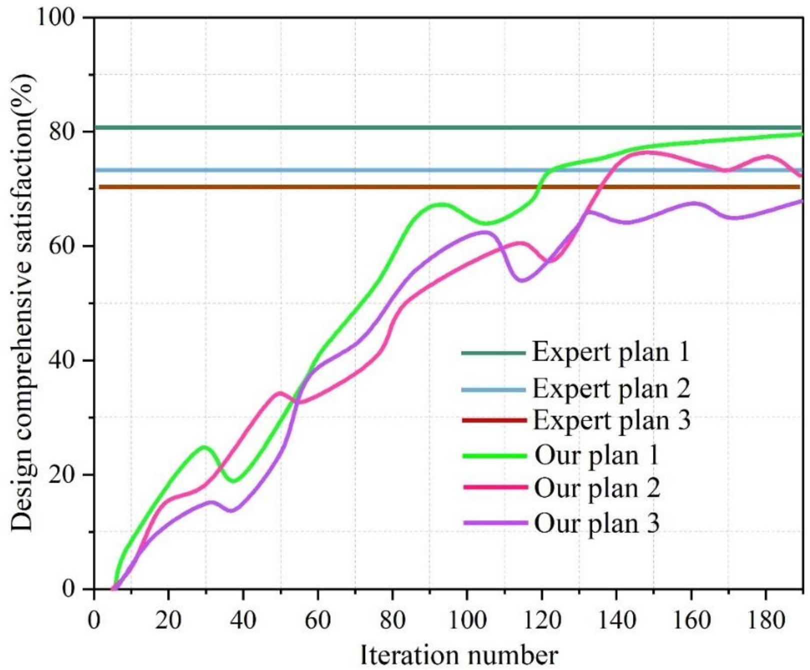


Figure 5. The comparison results of the design comprehensive satisfaction rate.

2.3.4. Comparison of Results from Different Models

Taking the styling design of the transformed product of the ontology of non-heritage skills as an example, this paper selects the results of the model generated by CGAN, BEGAN and WGAN methods for comparison, and the results of the comparison of different models are shown in Figure 6. As can be seen from the figure, when the number of iterations reaches 190 times, the design comprehensive satisfaction rate of CGAN, BEGAN and WGAN is 75.85%, 67.22% and 71.15% respectively, which is lower than the design comprehensive satisfaction rate of this paper's design program design 85.36%. This shows that the design effect of the model in this paper is better.

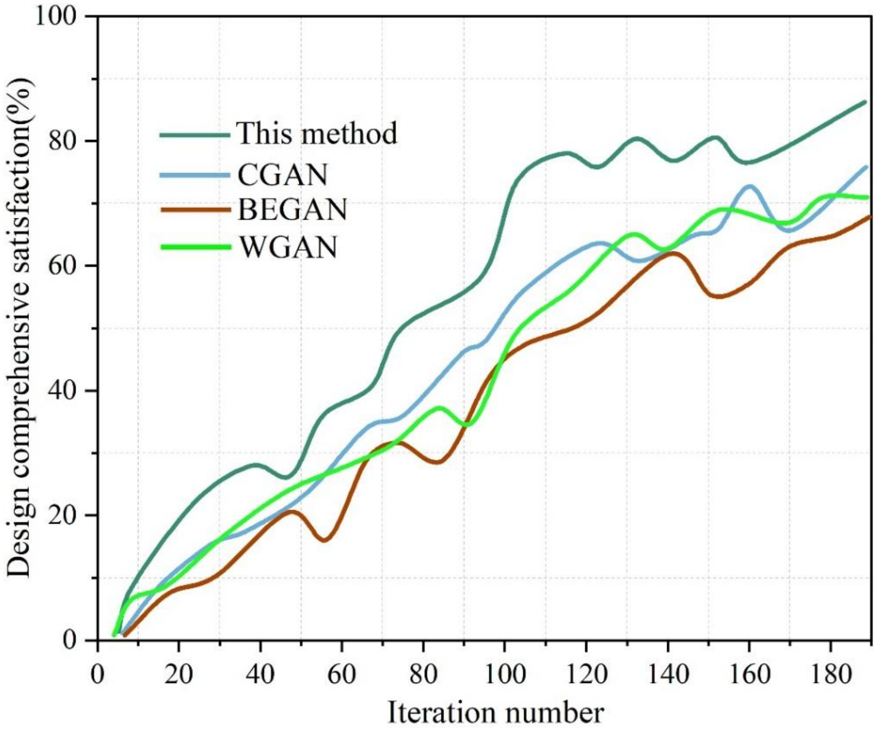


Figure 6. Different models compare results.

3. Optimization Method for Personalized Design of Non-Heritage Cultural and Creative Products

3.1. Product Personalization Design Based on Interactive Genetic Algorithm

3.1.1. Product Modeling Code

In this paper, the solution problem of product styling design is represented by a set S of morphological parameters. Namely:

$$S = \{p_1 \quad p_2 \quad p_3 \quad \cdots \quad p_n\} \tag{4}$$

where: S is the set of morphology parameters; $p_1 \sim p_n$ are all the independent parameters defined by all the designers defining the product styling, for example, the example in this paper verifies the 6 styling parameters of the non-heritage cultural and creative products. The definition domain of each parameter constructs an n -dimensional finite space, i.e., the solution space of product styling design, and the final solution process is to search the optimal solution in this space.

In this paper, we construct an operational method involving designers on top of the basic idea of genetic algorithm. Genetic Algorithm (GA) is a computational model that simulates Darwin's biological evolution process of genetic selection and natural elimination, and it is a method that searches for the optimal solution by simulating the natural evolution process, which is widely used in the solution of unstructured problems.

The interactive genetic algorithm involving designers can solve the problem of not being able to find the fitness function by adding designers' personal concepts in the process of solving the optimization search, and replacing the evaluation and selection based on the fitness function with the designers' choices. The solution space of product styling design is encoded into m levels, and in the corresponding sub-solution space on each level, the search and solution is carried out by using the interaction mode with the participation of the designers, and the results are fixed after completion, and the search and solution process just now is repeated by entering the space on the next level. The key to this search method is to determine the form of the solution space and subcodes at each level.

The set of morphological parameters in Eq. (4) is divided into m levels:

$$\begin{cases} S_1 = \{p_1^1 p_2^1 p_3^1 \cdots p_{n1}^1\} \\ S_2 = \{p_1^2 p_2^2 p_3^2 \cdots p_{n2}^2\} \\ S_3 = \{p_1^3 p_2^3 p_3^3 \cdots p_{n3}^3\} \\ \vdots \\ S_m = \{p_1^m p_2^m p_3^m \cdots p_{nm}^m\} \end{cases} \tag{5}$$

Eq. $S = S_1 \cup S_2 \cup \cdots \cup S_m ; n = n_1 + n_2 + \cdots + n_m$.

In this study, the original solution space is divided into different tiers and solved in the order from top to bottom. Corresponding to the conventional design solution method, for the design of styling according to the importance of each part of the design of the product first consider the main styling parameters, and then the secondary styling parameters, which is an important reference basis for determining the hierarchy.

3.1.2. Establishment and Solution of the Hierarchy

Parameter weight refers to the influence or importance of each part of the morphological parameters in product styling design on the overall design scheme, which is the main basis for constructing the coding of each level. In this paper, we adopt the method of interactive selection with the participation of target customers to determine the parameter weights, and the process is as follows: find a group of samples of target consumer groups as the product customer objects participating in the styling design method based on interactive genetic algorithm, randomly select a certain number of styling solutions in the original solution space, and then let the customers choose a number of satisfactory solutions from them. The command program records the parameter codes of each solution and the number of times it is selected, and the final selection results are analyzed by the program for analyzing the order of parameter weights.

In the process of determining parameter weights in a hierarchical manner, parameters with higher weight values should be prioritized, and other parameters related to them are automatically adapted to changes in parameters with higher weight values. The weights of all parameters are drawn and the weight coefficients w_i of the parameters are calculated as:

$$w_i = \sigma_i / \overline{E_i} \tag{6}$$

$$\sigma_i = \sqrt{\frac{\sum_{j=0}^{N_i} (p_j^i - \overline{E_i})^2}{N_i}} \tag{7}$$

$$\overline{E_i} = \frac{1}{N_i} \sum_{j=0}^{N_i} p_j^i \tag{8}$$

where: σ_i is the standard deviation of the curve; $\overline{E}_i$ is the mean of the curve; p_j^i is the number of times the value of the parameter i has been selected in the j th interval; and N_i is the number of times the parameter i has been selected.

The parameter value $p_{i\max}$ is also calculated for each curve peak:

$$p_{i\max} = p_i \mid S = S_{\max} \, , \tag{9}$$

After calculating the weight values of all the parameters and sorting them, the parameter coding expression for the new product styling design scheme is obtained as:

$$S' = \{p_1' \quad p_2' \quad p_3' \quad \cdots \quad p_n'\} \tag{10}$$

where: S' is the reordered set of morphology parameters; $p_1' \sim p_n'$ is the result of reordering the parameter values of the original product styling solution in accordance with the weights w_i from the largest to the smallest. The hierarchical segmentation form of the sorted product styling design solution space is:

$$\begin{cases} S' = \{S_1', S_2', S_3', \cdots, S_m'\} \\ S_1' = \{p_1', p_2', p_3', \cdots, p_{n_1}'\} \\ S_2' = \{p_{n_1+1}', p_{n_1+2}', p_{n_1+3}', \cdots, p_{n_1+n_2}'\} \\ \vdots \\ S_m' = \{p_{\sum_{i=1}^{m-1} n_{i+1}}', p_{\sum_{i=1}^{m-1} n_{i+2}}', p_{\sum_{i=1}^{m-1} n_{i+3}}', \cdots, p_{\sum_{i=1}^{m-1} n_{i+m}}'\} \end{cases} \tag{11}$$

where: $S' = \{S_1', S_2', S_3', \cdots, S_m'\}$ is the overall solution space including the sub-solutions space of $1 \sim m$.

where $S_1', S_2', \cdots, S_m'$ defines all levels of hierarchical solution space of the modeling design scheme. Using the method in this paper, the solution starts from the first level and uses an interactive genetic algorithm with the participation of designers to gradually solve the parameter values of the morphology encoding at all levels.

3.2. Product Personalization Design Based on Improved Interactive Genetic Algorithm

Users evaluate the adaptation value of an individual through IGA, and the long time and large amount of repetitive evaluation will inevitably cause user fatigue, so it needs to be optimized and improved. First of all, from the perspective of users' knowledge of the population, the whole population is gradually evolving from simple to complex, and the population in the initial stage is relatively simple, so the knowledge about the population acquired by users is also relatively simple, which can effectively avoid inaccurate evaluations of the evolved population due to the limitations of users' knowledge of the population; Second, from the perspective of product configuration, users can also gradually participate in the product configuration process just like designers.

Assuming that $f_n(x)$ is the fitness of an evolving individual x evaluated by the user, S is the search space of the individual x, and n denotes the stage of population evolution, the algorithm is optimized by finding the maximum value of the fitness:

$$\max f_n(x) \; x \in S \tag{12}$$

3.2.1. Improved Design for Variant Individuals

In order to allow the population to improve the local search efficiency based on obtaining good individuals in the process of evolution, and to maintain the variability of individuals to prevent the occurrence of early convergence, the mutation operator is improved. The probability of variation of individuals in the population:

$$P_m(x_i(t)) = 1 - (1 - p_m)^L \quad i = 1, 2, \cdots, N \tag{13}$$

where p_m is the probability of the original variation; L is the length of the bit string.

For a given uniform random variable $x \in [0,1]$, if $x \le P_m(x_i(t))$ then the individual produces variation, and vice versa.

It should be ensured that the expected number of traditional mutation probabilities (nLp_m) for the entire population is the same as the expected number of new gene mutation probabilities $(nP_m(x_i(t))Lp_m^{'})$, i.e.,:

$$nLP_m = nP_m(x_i(t))Lp_m^{'} \tag{14}$$

Among the results produced by the selection and crossover of the population in the first s generation, the expression for the random mutation operation on the selected individuals is:

$$p^{''}(s) = m(p^{''}(s), p_m) \tag{15}$$

Since $P_m(x_i(t)) < 1$, the new mutation approach reduces the computational effort compared to the traditional mutation approach. In order to obtain more suitable mutant individuals, the most suitable mutant individuals are obtained by introducing the golden section mutation:

$$\begin{gathered}\max(f(x_i^{-1}+0.618(x_i^{-1}-a_i)), f(x_i^{-1}+0.618(b_i-x_i^{-1})),\\ f(x_i^{-1}+0.382(x_i^{-1}-a_i)), f(x_i^{-1}+0.382(b_i-x_i^{-1}))),\\ x_i \in [a_i, b_i]\end{gathered} \tag{16}$$

3.2.2. Improved Design for Genetic Manipulation

For genetic manipulation, with the new module, there will be two steps:

(1) Selection of evolved individuals that are highly adapted at the final stage of each population. To wit:

$$P(x_i^{'}(t)) = \frac{f_n(x_i^{'}(t))}{\sum_{j=1}^{N_i} f_n(x_i^{'}(t))} \tag{17}$$

where $f_n(x_i^{'}(t))$ is the fitness value of individual $x_i^{'}(t)$; N, is the size of the population in each generation; s is the s th generation of the population; and $P(x_i^{'}(t))$ is the selection of individual $x_i^{prime}(t)$ probability.

Calculate the probability of selecting each evolved individual instead of selecting it directly in the final stage.

(2) Select the new genotype module. The allele fitness of the new genotype module is not fixed, so the user preference is determined by the individuals selected in the first step. The system will search for users with similar preferences and generate alleles based on the evaluated values from step (1).

After the above steps, the last generation of evolved individuals corresponds one-to-one with the randomly selected genotype template and the first generation population of the new stage is generated accordingly.

3.2.3. Improved Algorithm Flow

Compared with the traditional IGA, the control parameters of the proposed algorithm are set according to different evolutionary stages; the algorithm is easier to determine the number of evolutionary generations for termination than the traditional IGA, which reflects the core features of genetic algorithms. In addition, when entering a new stage, the system searches for users with similar preferences to realize collaborative evolution of multiple users to reduce user fatigue and improve local search efficiency.

3.3. Solution Based on Improved Interactive GENETIC Algorithm

Among all the generative rules, the rules are selected sequentially to obtain the preliminary frontal modeling morphology of the lathe, while the coordinate parameters required to describe each feature are obtained and genetically encoded using the binary multiparameter cascade coding method. In MATLAB, the GUI module is used to establish the interactive evaluation interface. Set the maximum number of genetic generations as 1100, the number of interval generations as 60, the generation gap as 0.95, the crossover probability as 0.95, and the mutation probability as 0.01, and end the evolution by obtaining a satisfactory solution at the time of interacting evolution to 700 generations.

After 700 iterations, the change of the mean value of the population objective function and the change of the optimal solution are shown in Fig. 7. Because the range of manual scoring is from 0 to 10 points, which is not the same as the range of fitness values calculated by the fitness function for the functional constraints, the fitness values fluctuate greatly at every 50 generations. The change in the mean value of the population fitness value and the change in the highest fitness value of the satisfactory solution for each manual assignment are analyzed separately. The changes in the mean value of the population objective function and the optimal solution are shown in Fig. 8. It can be seen that, whether it is the mean value of the population or the highest rating of the satisfactory solution, the method of this paper evaluates the assigned value fluctuates but has a general upward trend and obtains the satisfactory solution before reaching the maximum number of hereditary generations, which illustrates the validity of the model of the product morphology derivation.

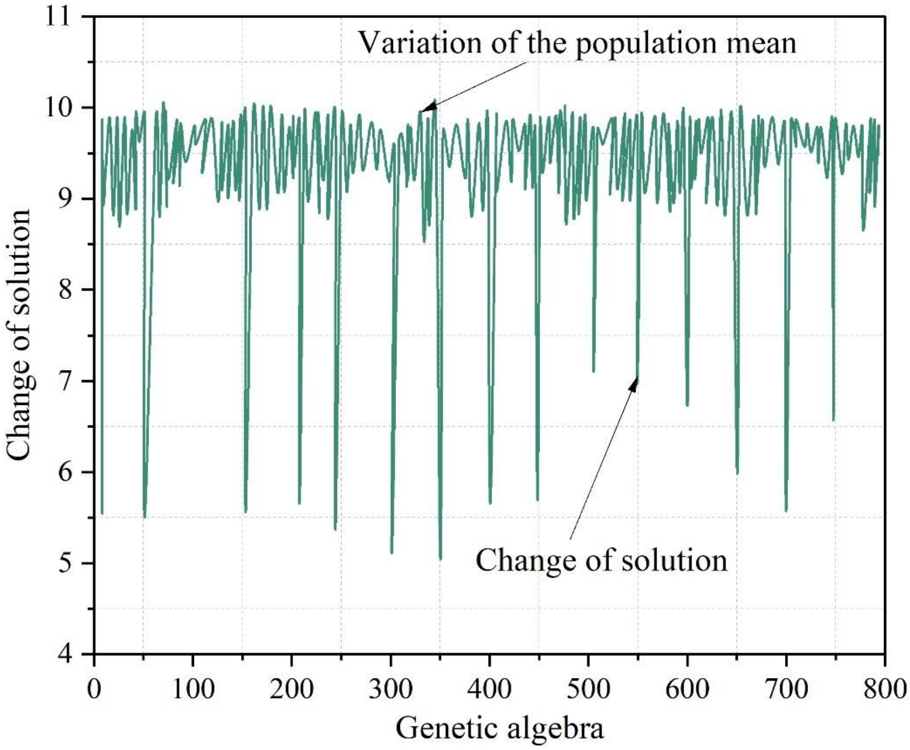


Figure 7. The mean of the population target function and the optimal solution.

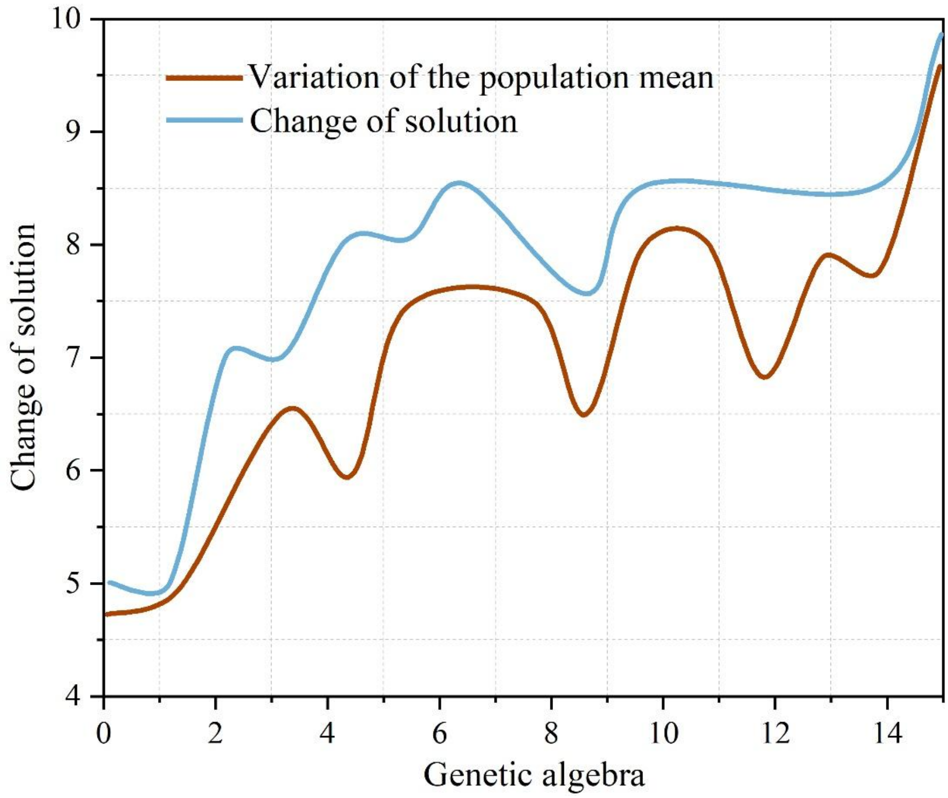


Figure 8. The mean of the population target function and the optimal solution.

3.4. Analysis of Experimental results of Modeling Evolutionary Design

The following experimental example takes the imagery semantic "cool" as an example, and after several experiments in this paper, it is found that when the genetic termination number is set to more than 200 generations, homogenization will occur in the evolutionary evolution of the shape. In order to avoid homogenization and enhance the diversity of form creation, the termination number parameter is reduced. After several attempts, it is determined that the modeling derivation with the following parameter settings satisfies the perceptual and aesthetic needs and meets the requirements of morphological diversity. The algorithm implements a termination algebra of 100; the population size is taken as 50; the crossover probability is 0.8; and the variation rate is 0.1. The adaptation values of the evolutionary experiment results are shown in Fig. 9. The coordinate parameters of the evolutionary design scheme are shown in Table 1. At the beginning of the evolution of 5 generations of fitness value rises dramatically, after the numerical change tends to stabilize the rise of linear, when the iteration to 85 generations, the fitness value is gradually stabilized, the highest value of 1.5686. Based on the above algorithm obtained by the fitness value tends to be high value screening and combined with the interactive evaluation, and ultimately selected a satisfactory modeling contour line, and will be used as a modeling concept of the subsequent design scheme for derivation.

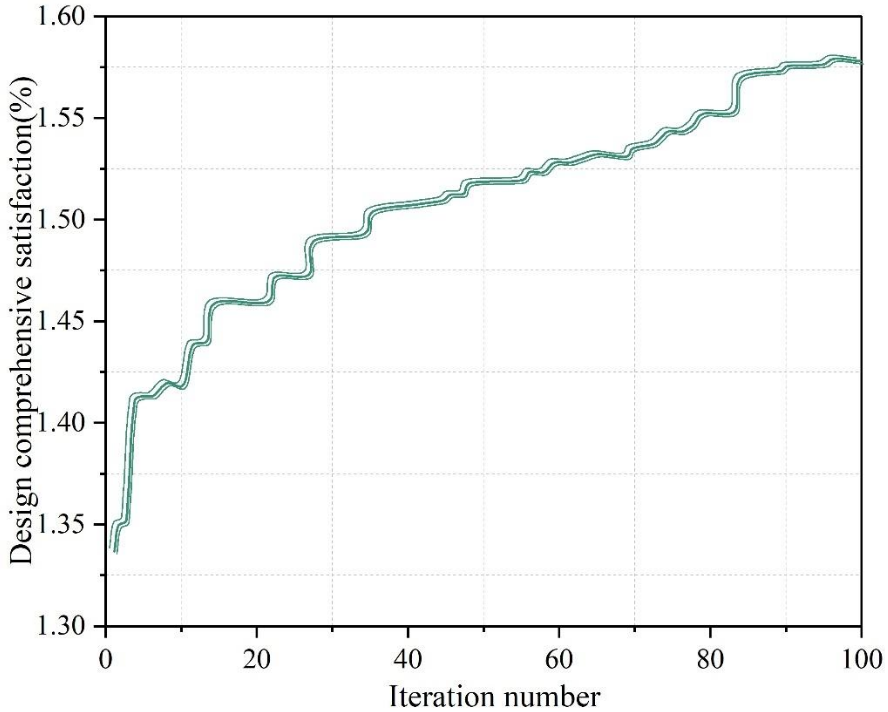


Figure 9. The adaptive value of evolutionary experimental results.

Table 1. The parameters of the evolutionary design.

Characteristic point coordinates	Solution 1		Solution 2		Solution 3	
	x	y	x	y	x	y
P_1(x, y)	311.25	0	311.25	0	311.25	0
C_1(x, y)	236.35	51.65	238.58	70.61	250.87	42.23
P_2(x, y)	241.7	88.46	234.21	110.84	232.45	79.57
C_2(x, y)	175.75	724.41	172.33	583.53	144.54	184.1
P_3(x, y)	217.67	752.33	244.87	752.41	243.91	557.25
C_3(x, y)	235.17	745.31	273.71	754.38	264.88	610.57
P_4(x, y)	486.24	742.96	353.57	743.65	430.58	891.29
C_4(x, y)	766.39	704.65	1239.03	700.17	993.54	884.13
P_5(x, y)	1569.13	547.73	1558.34	531.28	1685.36	608
C_5(x, y)	1734.2	458.16	1730.16	448.88	1836.38	589.02
P_6(x, y)	1832.71	226.93	1830.23	340.33	1862.31	438.09
C_6(x, y)	1923.8	203.56	1913.74	203.58	1925.47	200.44
P_7(x, y)	1937.97	171.84	1924.49	174.31	1925.97	169.5
C_7(x, y)	1869.7	35.64	1872.88	35.13	1876.77	18.47
P_8(x, y)	1851.48	0	1851.48	0	1851.48	0

4. Methods of Transforming Design Elements of Cultural and Creative Products from Rural Cultural Resources

4.1. Element Extraction and Innovation of Non-Heritage Cultural and Creative Products

With the booming development of the market of non-heritage cultural and creative products, rich culture and innovation and creativity have been the basic attributes of cultural and creative products. If you want to stand out in the market of many cultural and creative products, you also need to make a breakthrough in creativity, unique features, highlighting the creativity of cultural and creative products is crucial in the process of designing and developing rural cultural and creative products, which requires digging out and strengthening the characteristics of the products. You can work on the "shape" of the product, looking for interesting forms that match with the cultural and creative products, and you can also use exaggeration, deformation and other techniques to cartoon, fun image performance for creative design.

4.2. Reorganization and Deformation of Elements of Non-Heritage Cultural and Creative Products

There are many ways to express the elements of cultural and creative design, among which the most common is to extract and transform the design elements figuratively and abstractly through element reorganization. Element reorganization is the process of using the repetitive aesthetics and changes of elements to complete the reconstruction of the picture in cultural and creative design.

The reorganization and transformation of design elements usually involves the extraction and integration of different design elements in the form of breaking up, reconstructing, arranging and combining single graphic elements or single elements of combined graphics, so as to make the design elements more programmed and patterned, and to produce interesting and connotative picture effects. In the specific design method, the design elements are re-enlarged, or reduced, or deformed, or extracted from local elements, etc., to achieve the visual transformation of form and meaning.

4.3. Transplantation and Grafting of Elements of Non-Heritage Cultural and Creative Products

Element transplantation and grafting of cultural and creative products is an element transformation method often used in product styling design. When designing and creating, designers usually take natural objects as design prototypes, and through breaking and reorganizing the graphic elements, extract some of them that are similar to the product and graft them onto another object to form a new artistic image. The grafting of the object can emphasize the function of the two elements at the same time, so the form of this product will be a highlight in the cultural and creative design method.

5. Conclusion

This paper proposes a product personalization generation model based on improved interactive genetic algorithm for personalized design of non-heritage cultural and creative products, and proposes a method of design element transformation to reshape rural cultural resources. The results show that:

(1) When the number of iterations of the generative model in this paper is 190 times, the satisfaction rate of the pictures generated by the three models of non-heritage skill ontology transformed products and non-heritage elements creative derivatives products reaches more than 70%. And when the number of iterations reaches 190 times, the comprehensive satisfaction rate of the images designed by this paper's program is the highest (85.36%), and the design effect of the model is good.

(2) Whether it is the population mean or the highest rating of the satisfactory solution, the evaluation assignment of this paper's method fluctuates, but the overall trend is upward, and the satisfactory solution is obtained before reaching the maximum number of genetic generations, which illustrates the effectiveness of the product morphology derivation model. And when iterating to 85 generations, the value of fitness gradually stabilizes and finally reaches the highest value (1.5686).

(3) The method in this paper can complete the product design expression process quickly and efficiently, provides a reference framework based on deep learning technology for product design expression, and is also an innovative exploration of traditional product design in the era of artificial intelligence.

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