Research Article

Research on Style Design of Suit Based on Computer Interactive Genetic Algorithm

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In order to study the suit style design based on computer interactive genetic algorithm. Firstly, this paper summarizes the development status of garment customization and interactive evolutionary computing and studies the steps and system flow of customized garment design based on interactive evolutionary computing and the automatic generation method of garment style. Then, taking the suit as an example, the principal component analysis method is used to extract the elements of clothing design and code it. Combined with the interactive genetic algorithm, the user-satisfied clothing style binary string is generated, and the style binary string is decoded into a visual style map through the decoding algorithm. Finally, based on MATLAB platform, a customized clothing system prototype based on interactive evolutionary computing is realized. Users can carry out innovative clothing design through interactive graphical interface, automatically draw the clothing style designed by users, and provide method and technical support for clothing customization. The experimental results show that in the process of interaction design, try to solve the initial population required by the design, evolve and derive offspring on a large scale through genetic operation, retrieve the whole design feasible region, and obtain the optimal solution in line with user preferences.

1. Introduction

With the wide popularization of e-commerce, consumers' personalized demand for products is becoming stronger and stronger. The traditional customization generation mode has a long production cycle and monotonous style, which cannot meet the needs of consumers. Therefore, it is necessary to provide a personalized product customization platform to realize zero distance interactive customization with users, reduce production costs for enterprises, and improve user consumption satisfaction. Personalized product customization must have detailed theoretical and methodological support and technical guidance.

Fashion design is a creative act to solve the problem of dressing in people's life. It also uses the form of beauty to combine points, lines, and surfaces to construct a perfect shape. In the past, fashion design relied on the professional knowledge of fashion designers [1]. The imagination of fashion designers

is novel, abstract, and diverse. Fashion designers combine the intention they want to express with excellent fashion professional technology to form a fashion design process. The emergence of fashion design system enables ordinary users to design clothes and express their ideas in fashion design, so that fashion design is no longer the exclusive of fashion designers, and ordinary users can enjoy the sense of achievement of designing their own satisfactory works as designers (Figure 1). Therefore, combining fashion design with fashion customization, fashion design can provide some decision-making help in the process of user customization, describe the user's purchase preference through the clothes designed by a user, and customize the clothing products with satisfactory design for users. Provide users with personalized service platform experience integrating customization and design, which can not only facilitate users' customization, but also enable them to participate in the customization process and enjoy the customization experience, save human and
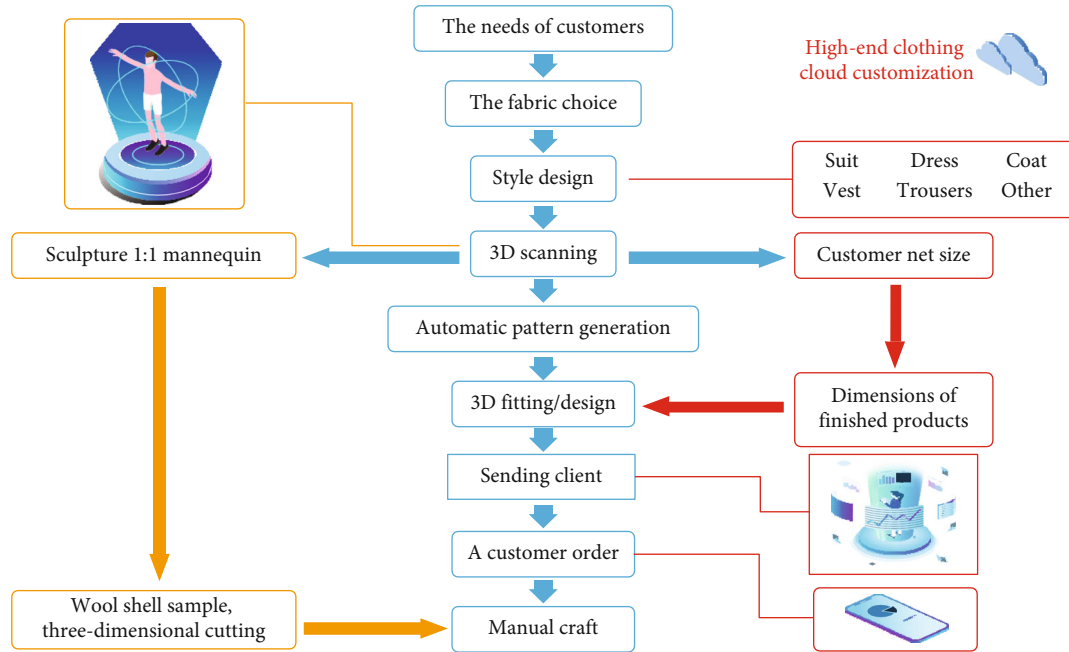
FIGURE 1: Suit Design process.

material resources, shorten the clothing design cycle, improve users' satisfaction, and improve the ordering rate of clothing customization and strengthen users' stickiness.

At present, the existing personalized custom clothing design system generally requires users to choose their favorite clothing styles and then randomly combine the clothing styles selected by users to form an overall clothing. In the face of many clothing styles, users only arrange and combine their Xinyi styles repeatedly, and do not realize the user's innovative design. With the long-term contact between users and clothing, each user has his own opinions and needs for clothing. The simple random combination of new clothing matching cannot fully meet the needs of users. In order to meet the needs of customers and improve the competitiveness of the market, users are required to participate in the design process. Therefore, this paper proposes an innovative design method of clothing through interactive evolutionary computing to meet the needs of user customization and enhance market competitiveness. The core of this method is to code and design the clothing design parameters based on the clothing design elements, convert them into binary strings through the coding algorithm, and combine the interactive genetic algorithm [2], generate the binary string of clothing style and style satisfactory to the user according to the clothing style information loved by the user, and decode the binary string of style and style into a visual style map through the decoding algorithm. Automatically draw the corresponding suit style map, complete the automatic innovative design of clothing, generate new styles that are not available in the system, and let the user experience become the existence and satisfaction of designers to complete the clothing design independently. Therefore, this research has important theoretical significance and practical application value [3].

2. Literature Review

Feng, Z. and others believe that clothing style comes from artistic style and has the essential characteristics of artistic style. According to the understanding of style at this stage, clothing style is the creative personality reflected in the creative process after the clothing designer fully understands a creative theme. It is the reflection of the accurate description of objective phenomena and the stable personality reflected by the designer in the long-term creative process [4]. Weiwei, Z. and others analyzed the clothing style from the style and studied the influence of different sizes of various parts of the clothing on the style [5]. Chao, H. and others proposed a variational averaging unit method to segment the image and evaluated the image candidate atlas generated by encoding the image feature data to obtain the image required by the user. In order to make the architectural design perfect [6], Yuan, G. and others successfully applied interactive genetic algorithm to the field of architectural design, which effectively promoted the further development of China's construction industry [7]. Similarly, Chao, H. and others have successively applied interactive genetic algorithm to automobile modeling design and product configuration design [8]. Yuan, G. and others realized the effective integration of commodity clothing purchase and clothing personalized design based on SSI with the help of the Internet. Combined with RIA technology and clothing CAD technology, they established an online customization system of clothing e-commerce system integrating online fitting, clothing sales, and clothing personalized customization. The system uses B/S mode and pixel bend: For image processing technology, solve the problem of slow pixel speed, realize the personalized fabric pattern design and color personalized requirements, and provide technical support for garment
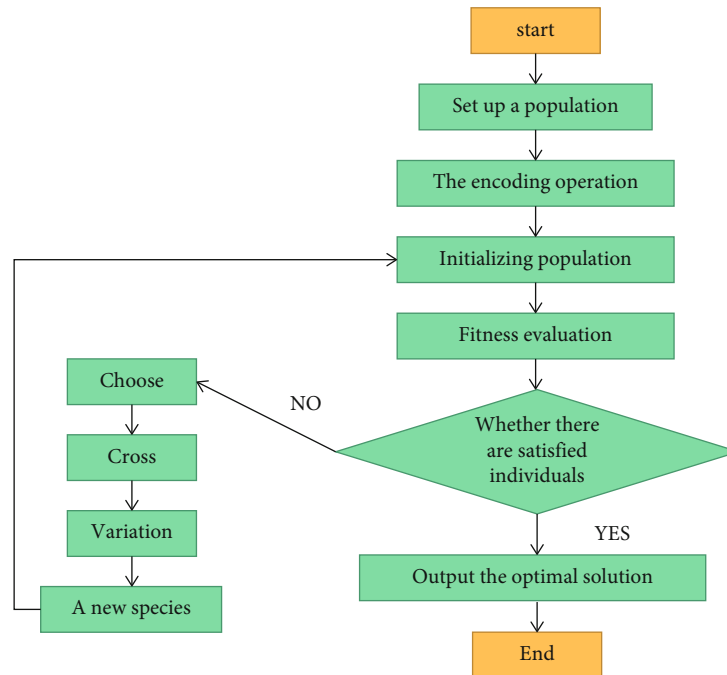
Figure 2: Algorithm flow.

customization [9]. Chen, J. W. and others analyzed the connotation and characteristics of traditional advanced customization and existing online garment customization by using the method of comparative analysis. Combined with the needs of consumers and computer technology, they designed a computer garment design system based on remote advanced customization, which solved the needs of single style selection and fit of traditional customization. However, there are too many size determination information in the customization process, which requires a large amount of input from the user. Secondly, the user's selection is limited to the style parts existing in the system. Arranging and combining them cannot generate new style parts not in the system [10]. In the research on the mode of clothing customization, Zhang, W. and others analyzed the purchase and sales background of clothing e-commerce and clothing customization customer group, studied the mode differences of customized clothing between China and foreign countries, and pointed out the problems existing in China's clothing customization. He pointed out that China's clothing customization innovation is insufficient and did not fully give users the opportunity to participate in design and other problems need to be improved [11]. Chen, L. and others analyzed the specific implementation process of personalized customized clothing and the advantages and disadvantages of related problems and put forward feasible improvement measures for online clothing customization [12]. In order to improve the customization experience of users, Meng, Y. and others studied and analyzed men's suits, optimized their customization process, developed a men's suit customization system, and carried out automatic customization design for the suit pattern. The main research object is the suit customization system developed for the user's body shape, and the style of customized clothes also exists in the system, Users only need

to choose to customize clothes based on their own body shape, which provides inspiration for the customized automatic design of clothes in this paper [13].

3. Interactive Genetic Algorithms (IGA)

The flow of interactive genetic algorithm is shown in Figure 2. The steps are as follows: ① population parameter setting; ② binary coding; ③ generate initial population; ④ decoding, users evaluate evolutionary individuals; and ⑤ judge whether the user has satisfied individuals. If so, output the optimal solution and the algorithm ends. If not, repeat the genetic operation to generate a new population, and turn to ③.

Three key features of the interaction design process are user-centered, specific usability standards, and iteration. User-centered, which is a core view of interaction design, allows users to participate in the whole design and evaluation and helps to get feedback in time. At the beginning of the project, specific usability and user experience objectives should be expressed and clearly explained, and requirements should also be agreed, which helps designers choose different candidate schemes and check them at any time in the process of product development. Through iteration, feedback can be used to improve the design. Iteration is inevitable because designers cannot find the correct solution at one time. Interactive genetic algorithm is the product of the combination of human-computer interaction and genetic algorithm. Its purpose is to combine human intelligence with computer technology to jointly solve the shortcomings in genetic operation. For example, in order to solve the decision-making model of clothing style, we must interact with users to obtain user information and then calculate it through genetic algorithm [14].

When using genetic algorithm (GA) to solve a problem, we need to first regard the possible solution of the problem as an individual in the population (population) and encode the individual into a symbolic string (i.e., chromosome). Then, the process of biological evolution is simulated, and the individual is repeatedly hybridized and mutated. Everyone is evaluated according to the predetermined fitness function, and new populations are obtained according to the evolutionary rules of survival of the fittest. At the same time, the optimal individual in the population is searched to obtain the optimal solution that meets the requirements. GA uses certain coding techniques to construct chromosomes: chromosomes are the basic objects of GA operation. When GA is executed, there are many individuals in each generation at the same time. GA program generates individuals in the new species group according to their adaptability to the environment. Individuals with strong adaptability have more opportunities to become individuals in the new species group. The adaptability is judged by the value of fitness function $f(x)$. The composition of fitness function $f(x)$ is closely related to the objective function, which is often a variant of the objective function. Genetic operations of GA include selection, crossover, and mutation. Selection is the process of selecting individuals with strong adaptability from the current population to produce a new population. When many individuals are the same or the offspring individuals are not much different from the previous generation, a new generation of individuals can be produced by hybridization.

For example, there are two individuals A and B, with a length of 8,

$$A = a1a2a3a4a5a6a7a8,$$
$$B = b1b2b3b4b5b6b7b8. \tag{1}$$

After hybridization, it may become A' and B':

$$A = a1a2a3a4|a5a6a7a8,$$
$$A' = a1a2a3a4|a5a6a7a8,$$
$$B = b1b2b3b4|b5b6b7b8,$$
$$B' = b1b2b3b4|b5b6b7b8. \tag{2}$$

Variation is the change of a gene in an individual with a very small probability. The combination of variation, selection, and hybridization can better ensure the effectiveness of GA. Interactive genetic algorithm is a new algorithm developed based on traditional genetic algorithm. The main difference between interactive genetic algorithm and general genetic algorithm is that IGA uses user interactive evaluation instead of the fitness function in traditional GA to select individuals.

3.1. Research on Interactive Genetic Algorithm Model

3.1.1. Clothing Code and Population Initialization. To use genetic algorithm, coding is not only the primary problem to be solved, but also an important step in the design of genetic algorithm. The coding method will directly affect

TABLE 1: Collar classification code.

Garment parts	Simple classification	Code classification	Code
Collar	No collar	No collar	0000
		–Word collar	0001
		Round neck	0010
		V-neck	0011
	Stand collar	Small stand collar	0100
		Gao Liling	0101
		Big stand collar	0110
	Lapel	Green fruit collar	0111
		Small lapel	1000

the operation of genetic operators such as crossover operator and mutation operator, which determines the efficiency of genetic evolution to a great extent. In fashion design, fashion style is expressed by designers through the combination of various fashion modeling elements. Although the modeling of clothing is changeable, its foundation, like all plastic arts, is the four morphological elements of point, line, surface, and body. Through the division, combination, accumulation, and arrangement of their base wood forms, clothing shapes with different styles and forms are produced. The degree of influence on the overall style, from strong to weak, can be determined as collar, piece, sleeve, dividing line, and accessories. The proportion of influencing style trend is approximately 50%, 30%, 15%, 4%, and 1%, respectively. Because the division line and accessories are too flexible and unrepresentative, in the initial exploration of style quantification, only the main parts of collar, piece, and sleeve are studied to find a feasible method of style quantification [15].

Due to the limited number of samples of clothing judged by experts, in order to classify the parts and facilitate the operation of parts classification when coding the parts, according to the collar type, it can be divided into collarless collar, stand collar, lapel collar, hat collar, and lapel. For these five collar types, combined with the information provided by experts, they are divided into 16 categories, as shown in Table 1. Similarly, Tables 2, 3, and 4 are the classification and coding tables of clothing length, sleeves, and pockets, respectively.

In this way, each garment top can be simply divided into four parts, and each part corresponds to a model, which facilitates the coding of parts and improves the operation efficiency. Take any coat as a chromosome to code the different parts of the garment. Clothing can be divided into four parts: collar type, sleeve type, length, and pocket. Each part is coded with four binary digits. The coding form is shown in Figure 3. Collar code, sleeve type code, length code, and pocket code are all in accordance with certain specifications. The number of digits of coding can be determined according to the type of clothing parts. This paper classifies the attributes of clothing according to the above. Use 4-bit binary coding for each part of the clothes.

The clothes selected by the user interaction module and the score are used as the input of the interactive genetic algorithm. Each clothes is a chromosome, and the total sample

TABLE 2: Clothing length classification code.

Garment parts	Simple classification	Code classification	Component code
		Below 45	0000
		46-48	0001
		49-50	0010
	Short	51-52	0011
		53-54	0100
		55-56	0101
Clothing length		57	0110
		58	0111
	In	59-60	1000
		61-62	1001
		63	1010
		64	1011
		65-66	1100
	Long	67-68	1101
		69-70	1110

clothes are used as the initial population of the genetic algorithm. As shown in Table 5, an example of the coding and scoring of IgA algorithm parts of a certain garment is given.

3.1.2. Fitness Design. After determining the coding specification of garment parts, the design of fitness function is the core of interactive genetic algorithm. Here, fitness can be regarded as the user's preference for a certain garment, and then, the preference for a certain garment can be extended to the preference for a certain part of the garment, which is determined by the style and score of the clothes selected by the user and the influence of the garment parts on the style. In this paper, the above components—collar type, sleeve type, garment length, and pocket—are used as gene combinations, so the chromosome fitness of garment components is as follows:

Suppose that the chromosome fitness of a part is R_i, the score of the clothing with the part is $Point_j$, the style influence degree of the part is $Part_i$($Part \in 50\%, 30\%, 15\%, 5\%$), and the total number of clothing with the part is $Sum = \Sigma j$ (i refers to the chromosome number of the part, and j refers to the clothing number containing the part). The fitness of the chromosome of a part can be calculated by the following formula:

$$R_i = \frac{\sum (Point_j * Part_i)}{\Sigma j},$$
$$C\_fitness = \sum Ri. \tag{3}$$

When each generation generates a new population, the fitness of existing parts remains unchanged, and only the fitness of the whole chromosome of each garment needs to be recalculated. In the new generation of generated population, there may be components that the user does not score. Currently, the component uses the average score of the user on the initial population to calculate its fitness.

3.1.3. Determination of Operators of the Algorithm. Selection operator is in the search process of genetic algorithm. The selection process reflects the idea of "survival of the fittest, survival of the fittest" in the process of biological evolution and ensures that excellent genes are inherited to the next generation of individuals. After consulting data and many experiments, the selection operator selected by the interactive genetic algorithm in this paper is the one with the highest fitness among several individuals selected by random tournament model, which is inherited to the next-generation population. The advantage is that there is no requirement for positive and negative individual fitness. This method has strong randomness and larger random error [16], but it has a large probability to ensure that the best individual is selected and the worst individual is eliminated. The number of individuals for each fitness comparison is the League scale N, generally $N = 2$. The process is as follows:

(1) Randomly select N individuals from the population for fitness size comparison, and inherit the individuals with the highest fitness to the next generation

(2) Repeat the above process M times to obtain M individuals in the next-generation population (where M is the population size)

The crossover operator randomly exchanges some genes between two individuals in the population according to the crossover rate, which can produce new gene combinations, hoping to combine beneficial genes together. Therefore, the setting of crossover operator reflects the accuracy of genetic algorithm to a great extent. From the point of view of the number of operation sites of crossover operator, genetic algorithm has experienced a process from single point crossover to two-point crossover, and from multipoint crossover to uniform crossover. Mutation operator refers to randomly selecting one or more loci for individual code strings in a population and changing the gene values of these loci. According to the existing data and repeated experiments, the genetic algorithm in this paper should adopt two-point crossover operator, the crossover rate is 0.8, the mutation rate is 0.01, and the termination condition is 200 generations specified in advance.

3.1.4. Establishment and Application of Decision Model. We will arrange the population after 200 generations of iteration according to the descending order of clothing chromosome fitness from high to low and select the first four items and corresponding fitness as the decision model to recommend clothing for users. The recommendation process is as follows:

$$\begin{aligned}
Model &= (A_{11}, A_{12}, A_{13}, A_{14})(Fitness\_1), \\
Model &= (A_{21}, A_{22}, A_{23}, A_{24})(Fitness\_2), \\
Model &= (A_{31}, A_{32}, A_{33}, A_{34})(Fitness\_3), \\
Model &= (A_{41}, A_{42}, A_{43}, A_{44})(Fitness\_4).
\end{aligned} \tag{4}$$

All clothes in the database have been coded in the form of $(B_1, B_2, B_3,$ and $B_4)$, and the coding of each part is 4-bit binary.

TABLE 3: Classification and coding of sleeves.

Garment parts	Simple classification	Code classification	Code
Sleeves	Sleeved, sleeveless, straight sleeve	No cypress	0000
		Middle sleeve	0001
		Changbai	0010
		Straight fear	0011
		Off shoulder sleeve	0100
		Round sleeve	0101
		Set-in sleeve	0110
		Two-piece sleeve	0111
	Food sleeve, raglan sleeve	Pagoda sleeve	1000
		Puff sleeve	1001
		Raglan sleeve	1010
		Tight mouth sleeve	1011

TABLE 4: Pocket classification code.

Garment parts	Simple classification	Code classification	Code
Pocket	Patch bag	Small patch bag	0000
		Large patch bag	0001
		Bright patch bag	0010
		Chest patch bag	0011
		Sleeve patch pocket	0100
		Flat patch bag	0101
		Oblique patch bag	0110
		Single side patch bag	0111
	Pocket insertion	Small pocket	1000
		Big pocket	1001
		Chest pocket	1010
		Sleeve pocket	1011
		Flat insert bag	1101
		Oblique pocket	1110
		Single side pocket insertion	1111

Traverse all the clothes in the whole database, and compare them with the model in turn to obtain the similarity value (the similarity degree of two chromosomes, the initial value is 0).

If $A_{ij} = B_j$, Similarly_value_j = Similarity_valuer $j +$, the influence degree of the part on the style is Fitness_i; $(i, j = 1, 2, 3, 4)$. Compare the clothing with the four lines of the model, and finally, get the similarity of the clothing as Similarly value = Max (Similarity value − j), $(J = 1, 2)$ $(j = 1, 2, 3, 4)$.

For example, the model results obtained by genetic algorithm are shown in Table 6:

At this point, there is a vector decision model:

$$
\text{Model} = \left\{ \begin{array}{cccc} 0110 & 1000 & 1111 & 1011 \\ 0110 & 0000 & 1111 & 0100 \end{array} \right\} \left\{ \begin{array}{c} 84.65 \\ 80.8 \end{array} \right\},
$$
$$
\text{Model} = \left\{ \begin{array}{cccc} 0110 & 0000 & 1111 & 0110 \\ 0110 & 0001 & 1111 & 0010 \end{array} \right\} \left\{ \begin{array}{c} 79.98 \\ 79.81 \end{array} \right\}. \tag{5}
$$

Take the code of any garment in the database as (0110100011011011), compare it with the four lines of the above model, and the similarity between the chromosome of the garment and the first line of the model is

$$
\begin{aligned}
\text{Similarity\_value\_1} &= 50\% * 84.65 + 30\% * 84.85 \\
&\quad + 5\% 84.65 = 71.95.
\end{aligned} \tag{6}
$$

Traverse the entire database, calculate the similarity between each garment and the model, sort the similarity from high to low, and recommend the first certain number of garments to users. Users' scoring of the initial clothing population may be affected by personal emotions and moods, such as excessive initial population, users' scoring irritability, and other factors. Different initial population numbers and average scores are used for 10 testers, as shown in Figure 4.

It can be seen from Figure 4 that after many tests and statistics, the effect is the best when the initial population number is set to 60. The clothing recommended by the model generated by Jingshan system from the database can meet the needs of users to a great extent, which also verifies that the interactive genetic algorithm can be better applied in the clothing style decision-making model.

The fashion design style decision-making model based on interactive genetic algorithm is that the user interacts with the system and obtains the user's subjective score on the clothing. Combined with the influence of various components on the fashion design style, the decision-making model of the fashion design style is obtained. Finally, according to this model, the clothing most likely to be favored by the user is obtained from the data base and recommended to the user [17].

3.2. Extraction of Clothing Style Based on Principal Component Analysis

3.2.1. Principal Component Analysis

(1) Basic Idea of Principal Component Analysis. In the empirical study of something, in order to more comprehensively and accurately reflect the characteristics and development law of things, people often have to consider multiple indicators related to it, which leads to the following problems: On the one hand, people consider as many indicators as possible in order to avoid missing important information. On the other hand, too many indicators are selected, which bring some difficulties to the research, and there may be some correlation between many indicators, which cause the overlap of information and affect the research results.

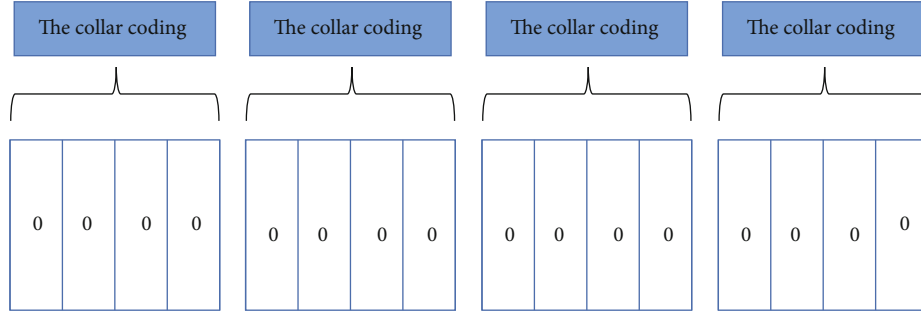Based on the above problems, researchers expect quantitative research to involve fewer variables and obtain more

Figure 3: Chromosome coding.

Table 5: Example of clothing coding and scoring.

Clothes	Collar type	Sleeve type	Clothing length	Pocket	Clothing code	User scoring
Grace NO.3	0010	1100	1010	1111	0010110010101111	87
Grace NO.4	0000	0010	1100	1111	000001011001111	65

Table 6: Model information obtained by algorithm.

Collar type	Sleeve type	Clothing length	Pocket	Clothing chromosome fitness
0110	1000	1111	1011	84.63
0110	0000	1111	0100	80.7
0110	0000	1111	0110	79.89
0110	0001	1111	0010	79.18

information. Principal component analysis is very popular for solving the above problems. It is a statistical analysis method that can simplify the total number of comprehensive indicators and solve the problems with good performance. By analyzing the relevant variables in the problem, and studying the internal structure relationship of the variable correlation matrix or covariance matrix, and then, using the linear combination of variables to form an important comprehensive index comprehensive index (principal component), its purpose is to reduce the dimension and simplify the problem before retaining the main information. It makes it easier to grasp the main relationship of things in the research process.

(2) Principle of Principal Component Analysis. From a mathematical point of view, principal component analysis is a multivariate statistical method that can convert multiple indicators into a few indicators through linear change. There are m samples, and each sample has n indicators to form a data matrix of $m \times n$ order (standardized data).

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{n2} & \cdots & x_{mn} \end{bmatrix}. \tag{7}$$
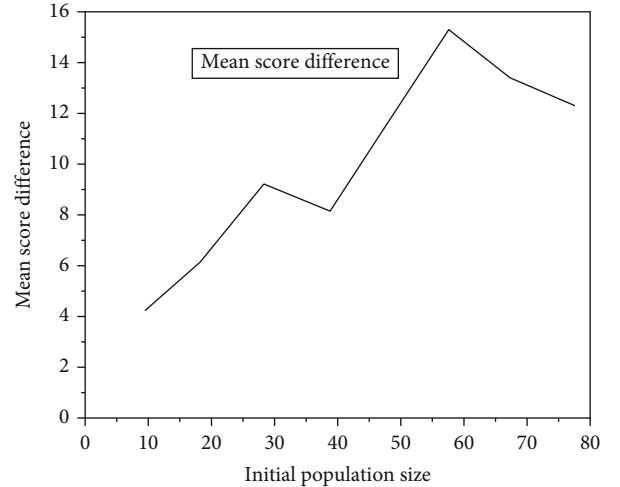

Figure 4: Relationship between initial population and mean difference.

When n is large, it is troublesome to investigate the problem in n-dimensional space. If there is an interactive relationship between the indicators, a small number of comprehensive indicators can be selected from the n indicators, and the smaller number of comprehensive indicators can be used to reflect most of the information of the original indicators as much as possible, and the information contained is independent of each other [18], which simplifies the problem and makes the data information results more scientific and effective. This analysis method is called principal component analysis method. In the research of practical problems, in order to analyze the problems comprehensively and comprehensively, we must consider many influencing factors to ensure the comprehensiveness and objectivity of the analysis of the problems studied. Therefore, many related indicators are proposed, and each indicator reflects some information of the research problems to varying degrees. Principal component analysis, also known as

principal component analysis, uses the idea of dimension reduction to reduce the dimension of multiple indicators, and extracts a small number of principal components from the original variables to represent the linear relationship between multiple variables. The cumulative contribution rate is used to reflect the correlation between each principal component and the original variables and to determine the weight of the principal component in the final evaluation.

(3) Principal Component Analysis Method. Using the "dimension reduction" process in the "factor analysis" of statistical analysis software spss20.0, this paper makes a principal component analysis on the clothing style. Through principal component analysis, the initial eigenvalue, principal component load value, principal component score coefficient matrix, and principal component comprehensive model of each component are obtained, and finally, the index weight is determined. Eigenvalue is one of the indexes to judge the principal component score, and it is also an index to affect the strength of the principal component. The principal component load value represents the correlation between the principal component and the original variable information.

There are three methods to determine the principal component score: (1) Select the principal component part with the corresponding eigenvalue greater than 1, because the eigenvalue greater than 1 indicates that the influence of the principal component is strong. If the eigenvalue is less than 1, it means that the interpretation of principal component decomposition is small, which is not as strong as the average interpretation of directly introducing the original variables. Therefore, the selected eigenvalue is greater than 1. (2) On the premise that the eigenvalue is greater than 1, select the principal component with the corresponding cumulative variance contribution rate greater than 80%. When the cumulative contribution rate is greater than 80%, it is enough to reflect the information of the original variable, and the corresponding m is the first m principal components extracted. (3) The number of principal components is determined according to the mutation point of characteristic root change. Compared with the original variables, the principal component obtained by principal component analysis has the following advantages: first, the principal component represents the linear relationship between the original variables; second, the number of principal components is greatly reduced compared with the original variables; third, the principal component retains most of the information of the original variables; and fourth, each principal component is independent and irrelevant [19].

3.2.2. Clothing Gene Extraction Based on Principal Component Analysis. Principal component analysis is a statistical method that tries to recombine the original variables into several independent comprehensive variables, and at the same time, it can take out several less sum variables to reflect the information of the original variables as much as possible. It is also a method of dimensionality reduction in mathe-

matics. Based on the modeling parameterization theory, there are 10 typical suit style samples, each sample has 73 variables, and the evaluation indexes of each sample are x_{ij}, i from 1, 2; 10; 1, 2,..., 73, 730 data in total. In order to facilitate the analysis and comparison of various indicators under the same standard, principal component analysis is carried out for the x-axis coordinates and y-axis coordinates of the matrix. The common method is to standardize x_{ij}, and remember that the matrix of each typical suit style sample after standardization is x.

$$x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_i \end{bmatrix}. \tag{8}$$

Each sample consists of 10 performance evaluation indexes. The comprehensive evaluation indexes obtained by linear combination are z_{ij} and b_{ij}, which are load coefficients. The matrix composed of b_{ij} is called the main component transformation matrix, which is recorded as b, namely

$$z_{ij} = \sum_{i=1}^{10} b_{ij} x_{ij},$$

$$b = \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1j} \\ b_{21} & b_{22} & \cdots & b_{2j} \\ \vdots & \vdots & \cdots & \vdots \\ b_{i1} & b_{i2} & \cdots & b_{ij} \end{bmatrix}. \tag{9}$$

If the comprehensive evaluation index matrix of sample composition is z, there are

$$z = \begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_i \end{bmatrix}. \tag{10}$$

The principal component transformation matrix b can be obtained by principal component analysis. Principal component analysis is a dimension reduction technology, which reduces the data in high-dimensional space to low-dimensional space, and saves most of the information in the original space as much as possible. Based on parametric characterization, the principal component contribution rate, cumulative contribution rate, and absolute value of principal component load at each point of x-axis and y-axis are calculated. The principal component contribution rates of x-axis and y-axis are shown in Tables 7 and 8, respectively, and the corresponding gravel diagrams are shown in Figures 5 and 6, respectively.

According to the principle that the eigenvalue in the determination method of principal component score is

TABLE 7: Principal component contribution rate of x coordinate axis.

Principal component	Characteristic value	Variance%	Cumulative%
1	21.403	29.333	29.323
2	20.218	27.653	57.012
3	10.224	13.004	71.230
4	5.747	7.856	78.887
5	3.846	5.321	84.184
6	3.222	4.532	88.786
7	3.12	4.260	94.056

TABLE 8: Contribution rate of y-axis principal components.

Principal component	Characteristic value	Variance%	Cumulative%
1	24.168	33.959	31.959
2	16.258	54.287	54.276
3	8.325	68.389	98.329
4	5.468	74.874	73.849
5	4.990	80.739	81.726
6	4.615	87.056	87.024
7	3.048	91.231	91.231

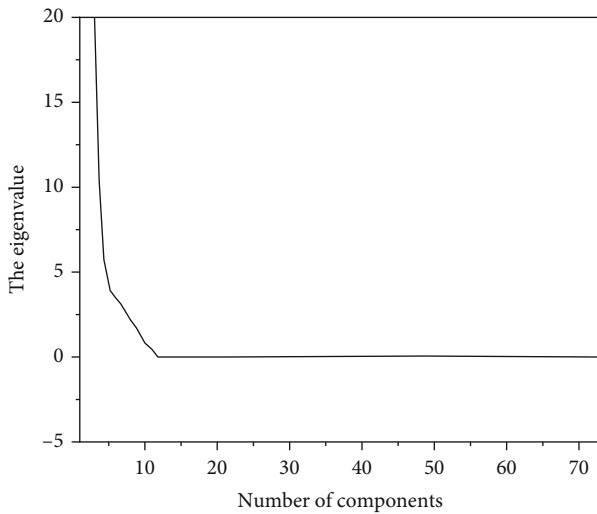FIGURE 5: Gravel diagram of x coordinate axis.

FIGURE 6: Gravel diagram of y coordinate axis.

greater than 1, select the principal component part with the corresponding eigenvalue greater than 1. It can be seen from the contribution rate of principal components on the x-axis (Table 7). The eigenvalues corresponding to the first, second, and third to seventh principal components are greater than 1, so there are seven principal components. On the premise that the eigenvalue is greater than 1, select the principal component with the corresponding cumulative variance contribution rate greater than 80%. It can be seen from Table 7 that the cumulative percentage of the eigenvalue corresponding to the first five principal components reaches
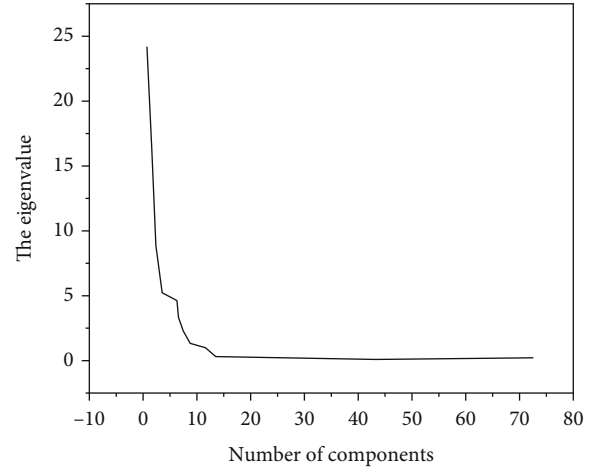
84.194%, which implies that if the five principal components are selected, the amount of information reflecting the original information is enough. Finally, according to the principle that the number of principal components is determined by the mutation point of characteristic root change, it can be seen from the broken line diagram of characteristic root distribution on the gravel diagram of x coordinate axis in Figure 5 that the fifth characteristic root value is an obvious break point, which implies that the selected principal component score should be $p < 5$.

According to the three number extraction principles of principal components, the contribution rate of y-axis principal components (Table 8) shows that the corresponding characteristic roots and cumulative variance contribution rate of the first five principal components meet the requirements. The characteristic root is greater than 1, and the cumulative variance contribution rate is 81.729% greater than 80%. At the same time, it can be seen from the broken line diagram of characteristic root distribution on the gravel map of y-axis in Figure 6 that the fifth characteristic root value is an obvious break point, and five principal components can be extracted. The first five principal components can replace the original seven indicators, which can basically reflect the information of all indicators [20].

4. Clothing Interactive Design Experiment

The system mainly completes the functions of customized clothing design. These functions mainly include parameter setting module, clothing evaluation module, genetic algorithm module, result display module, and database module. The specific functional modules are shown in Figure 7.

The parameter setting module defines the total evaluation times and the crossover and mutation probability of the algorithm. In addition, the "enter" button sends instructions to the database to jump to the evaluation display interface. The clothing evaluation module displays the blueprint of clothing data in the database, and checks box and scoring box transmit data to the database. Buttons are divided into three states: start, upload, next, and end. In addition, two
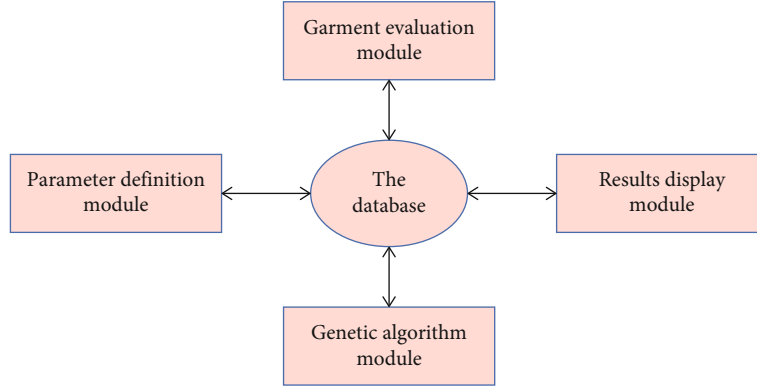
FIGURE 7: System module diagram.

TABLE 9: Average convergence algebra of satisfactory scheme evaluation with different parameters.

Parameter Scheme type	TS-IGA	TS-IGA
pc = 0.6 pm = 0.005	13	11.5
pc = 0.6 pm = 0.01	9.4	13
pc = 0.6 pm = 0.03	9	15
pc = 0.6 pm = 0.005	6.5	15.5
pc = 0.6 pm = 0.01	11	9.5
pc = 0.6 pm = 0.03	11	15.5
pc = 0.6 pm = 0.005	10	12.5
pc = 0.6 pm = 0.01	12	12
pc = 0.6 pm = 0.03	11	12

FIGURE 8: Algebraic line chart of convergence of satisfactory scheme evaluation with different parameters.

schemes of clothing model initialization are provided: one is typical style, and the second is random generation. Genetic algorithm module selects, crosses, and mutates the data through the clothing model, and the corresponding score provided by the database to obtain new clothing data. According to the instruction, upload the data to the database again or enter the evaluation module. The result display module displays the clothing model with the highest score in each clothing evaluation in the database, the score, and the current evaluation times. The database stores the algorithm parameters, initialization scheme type, data and score of clothing evaluated each time, and data, score, and evaluation times of clothing with the highest score.

4.1. Setting of Genetic Operator Parameters. In the interactive design of clothing, two parameters, crossover probability and mutation probability, are involved. Crossover, also known as hybridization, aims to produce new individuals. The crossover probability determines whether to cross two individuals and what kind of hybridization method to use. If the crossover probability is too large, it is easy to destroy the existing favorable model, increase the randomness, and easily miss the optimal individual, resulting in many problems in the evolution of population by genetic algorithm. If the crossover probability is too small to effectively update the population, the convergence
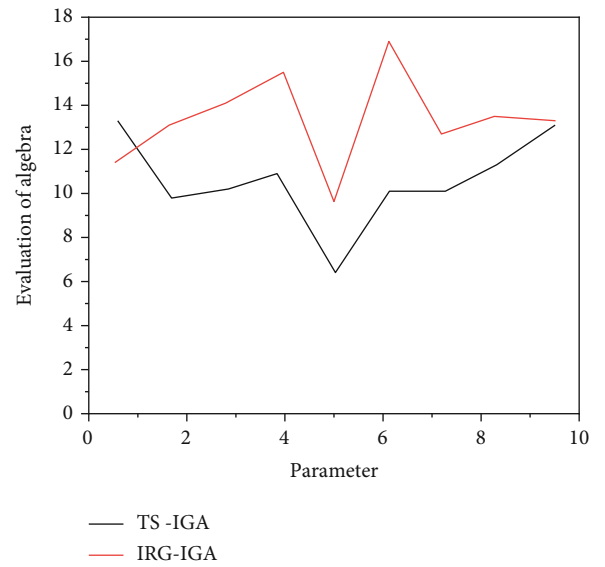
speed of the algorithm is slow, and the speed of generating new individuals is also slow, resulting in user evaluation fatigue. Generally, the selection range of crossover probability is 0.4-0.99, but why the crossover probability is worth passing the experimental test.

The purpose of mutation probability is to make gene mutation. In the optimization algorithm, it can prevent the algorithm from falling into local optimization, to jump out of local optimization and help the algorithm find the global optimal solution. Like the crossover probability, the mutation probability is too large. Although the diversity of the population can be guaranteed, the probability of high-order mode destruction also increases. If the mutation probability is too small and the diversity of the population decreases too fast, although it can keep the algorithm stable, it is easy to lead to the rapid loss of effective genes and is not easy to repair, reduce the generation of new individuals, and may not produce the optimal solution and terminate the algorithm. Generally, the selection range of variation probability is 0.0001-0.1. Like the crossover probability, the size of crossover probability must be known through experimental tests.

TABLE 10: Maximum score of each generation of testers.

Tester Algebra	One	Two	Three	Four	Five	Six	Seven	Eight	Nine	Ten	Satisfied algebra
1	4	4	5	7	7	8	8	9	10		
2	8	7	6	8	10						
3	6	7	7	8	8	9	10				
4	7	7	6	7	8	8	8	8	8		
5	8	6	6	9	9	9	9	9	9		
6	8	8	9	9	9	9	10				
7	7	7	7	8	5						
8	9	9	9	9	10						
9	8	7	8	8	10						

4.2. The Relationship between the Effect of Fashion Style Design and the Probability of Crossover and Variation. There are two types of initial schemes: One is typical style interactive genetic algorithm (ts-iga), and the other is randomly generated interactive genetic algorithm (rg-iga). In this paper, because the specific values of crossover probability and mutation probability cannot be determined, the trial method is used to make a comparative experiment according to a certain growth rate in the range of crossover probability and mutation probability and to determine the crossover and mutation probability values that make the algorithm reach the optimal solution. At the same time, the experimental comparison of the two initial schemes is carried out to verify the convergence of the two schemes. The test results are shown in Table 9.

In order to make it easier to see the change effect more intuitively in the process of analysis, the data in Table 9 are drawn into a broken line chart, as shown in Figure 8.

As can be seen from Figure 7, when the crossover probability is the same, the mutation probability value is 0.01, which can obtain the user's satisfactory scheme evaluation as soon as possible, and its average convergence algebra is relatively lower than that corresponding to other mutation probabilities. When the mutation probability is the same, the convergence rate with the crossover probability value of 0.8 is significantly higher than that corresponding to other crossover probabilities, and it can also be locally predicted that ts-iga converges faster than rg-iga. However, many experiments should be carried out after the crossover, and mutation probability parameters are determined to determine whether the prediction is correct.

Interactive genetic algorithm is an evolutionary optimization method that takes human subjective evaluation as evolutionary individual fitness and takes human subjective evaluation as the basis of evolutionary individual fitness assignment. The concept of interactive genetic algorithm has been effectively used to solve the index optimization of implicit performance. This index optimization cannot be calculated directly by function, but by uncertain factors such as customer preference. This method integrates human cognition into genetic algorithm by replacing the optimization objective function, in which human evaluation function takes part in the evolutionary process as an evolutionary

individual. Individual fitness value is completed according to many evaluations needs in human-computer interaction, but frequent interactive evaluation will make users feel tired, which can lead to the unavailability and inaccuracy of evaluation. According to the characteristics of interactive genetic algorithm, its research can be divided into two categories: one is to study the uncertainty of evolutionary individual fitness value. The second is to improve the algorithm and accelerate the convergence of the algorithm, to reduce user evaluation fatigue, to reduce evolutionary algebra, and to accelerate convergence algorithm.

Taking the two classifications as the guiding direction, this paper adopts two methods to alleviate the problem of user evaluation fatigue: the first method is to change the interactive evaluation order, evaluate before genetic operation, and take the user evaluation score in human-computer interaction as the fitness value, Second, assign the style of the product to the initial population; that is, set the typical style as the initial population, and change the probability parameters of crossover and mutation to reduce the evolutionary algebra, accelerate the convergence algorithm, and alleviate the evaluation fatigue of users.

Taking this parameter as the benchmark, in order to prove the effectiveness of the algorithm, several testers conducted comparative experimental tests. In order to judge the performance of the algorithm, we recorded their evolutionary algebra, the number of evaluation individuals, the size of score value, and their fitness value. The experimental results are compared and analyzed to verify whether this method can alleviate the problem of user fatigue.

Table 10 records the maximum score and satisfactory algebra of each tester in the evaluation of each generation in ts-iga. It can be seen from the data in the table that the first generation of convergence is the fourth generation, the latest generation is the eleventh generation, and the average number of satisfactory convergence generations of all testers is eight generations. At the same time, calculate the average value of the maximum score of testers in each generation. The average value of the maximum score of the first generation is 6.7 points. All testers are satisfied with the initial population generated by the system for the first time, and with the increase of algebra, the average score is getting higher and higher, gradually approaching the clothing style satisfied by users.

5. Conclusion

This paper studies the interactive fashion design system, starting from the research point of Western-style style modeling, and takes human-computer interaction as the main way to carry out the innovative design of clothing. According to the analysis of users' needs, the description of style is introduced, and the style of clothing is studied and applied to realize the expression of users' needs. Combined with the design characteristics of men's suits based on biological genes, the customized clothes are designed by using interactive evolutionary computation based on style description. Principal component analysis is used to extract and express the genes of typical style samples of Western-style clothes, obtain the principal component gene characteristics of style modeling of Western-style clothes, analyze their characteristics, and make a new gene definition, sort out the elements affecting fashion design, and carry out parametric design. For interactive genetic algorithm, on how to reduce user evaluation fatigue, this paper draws lessons from some research results of genetic algorithm in the industrial field and applies it to the research of clothing style. Therefore, this paper proposes an interactive genetic method based on typical style. For traditional genetic algorithms, their initial population is uncertain and randomly generated. In this paper, through the analysis of product style, the product style is assigned to the initial population, the typical style is set as the initial population, and the probability parameters of cross mutation are changed. The experimental results show that user fatigue can be greatly reduced.

Because the Western-style style modeling intention and genetic algorithm clothing design studied in this paper are mainly aimed at the shape design of clothing outline, that is, only a single factor of style modeling is considered, and the fabric, color, and details are not considered. Because the fabric, color and details of clothing also have a certain impact on the clothing style intention, the follow-up research can integrate these factors based on this study.

Data Availability

The labeled dataset used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no competing interests.

Acknowledgments

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