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Research on Enhancing the Efficiency of Combining Creativity and Craftsmanship in Personalized Garment Design Based on Intelligent Optimization Methods

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Abstract The application of intelligent optimization methods injects new vitality into personalized clothing design and effectively improves the efficiency of combining creativity and craftsmanship. In this study, the interactive genetic algorithm is used to optimize the process of personalized clothing design, and the method to enhance the efficiency of combining creativity and craftsmanship is explored. Considering the garment as a whole as a chromosome, the key elements are binary coded, and a single-point crossover mutation is used to continuously optimize the design scheme. The system realizes human-computer collaborative design through the user's subjective evaluation as an adaptation function, effectively overcoming the limitations of traditional design methods. The experiment selects 8 groups of initial populations, sets the crossover probability 0.6 and mutation probability 0.8, and invites 20 users to participate in the test. The results show that the interactive genetic algorithm can obtain higher aesthetics values compared with the traditional method, with an average improvement rate of 18.32% (comparing with the traditional genetic algorithm) and 35.06% (comparing with the two-dimensional crop method). The average fitness values for users to obtain satisfactory design solutions are all greater than 88.67, and the highest fitness value can reach 97. All users can obtain satisfactory results within 4-8 generations, and the average evolution reaches the maximum value of evaluation in the 9th generation, which is significantly better than that of the traditional genetic algorithm in 12 generations. The experiment proves that the method not only improves the efficiency of personalized clothing design, but also enhances the user's cognition of the system, realizes the efficient combination of creativity and craftsmanship, and provides a new idea for personalized clothing customization.

Index Terms personalized clothing design, interactive genetic algorithm, intelligent optimization, combination of creativity and craftsmanship, user satisfaction, adaptation evaluation

I. Introduction

Clothing design and production is a complex industry, and the traditional garment manufacturing process has to go through dozens of procedures, from fabric selection, sample garment sizing, tailoring, sewing, ironing, and so on, until the complete product is cut [1]-[3]. The popularity of modern technology has injected new vitality into the apparel design and production industry, and the application of intelligent optimization methods effectively improves the efficiency of personalized apparel design innovation and process combination, and improves the quality of apparel design and production [4]-[6].

In the traditional apparel design process, designers need to spend a lot of time on market research, sketching and fabric selection [7], [8]. Nowadays, the application of intelligent methods has greatly shortened this process. By accessing artificial intelligence tools, designers only need to input simple text descriptions or reference pictures, and then they can quickly generate diverse design sketches, which greatly saves time and cost [9]-[12]. The biggest advantage of the intelligent method is personalized clothing design. With the growing consumer demand for personalized products, the clothing customization market is gradually emerging, and the application of intelligent methods further promotes the development of this trend [13]-[15]. By collecting information such as consumers' body data, preferences, and wearing habits, intelligent methods are able to customize clothing to fit their personal style [16], [17]. This kind of personalized customization service based on big data analysis not only improves consumer satisfaction and loyalty, but also brings new growth points for apparel companies [18], [19]. At the same time, the intelligent method can also provide precise suggestions in fabric selection and pattern adjustment to ensure the comfort and aesthetics of customized clothing [20], [21].

Clothing design and production is a complex industry, the traditional garment manufacturing process has to go through dozens of procedures, from fabric selection, sample garment sizing, tailoring, sewing, ironing and other links, until the complete product is cut. The popularity of modern technology has injected new vitality into the clothing design and production industry, and the application of intelligent optimization methods has effectively enhanced the efficiency of personalized clothing design innovation and process combination, and improved the quality of clothing design and production. In the traditional apparel design process, designers need to spend a lot of time on market research, sketching, fabric selection and other aspects. Nowadays, the application of intelligent methods has greatly shortened this process. By accessing artificial intelligence tools, designers only need to input simple text descriptions or reference pictures to quickly generate diverse design sketches, which greatly saves time and cost. The biggest advantage of the intelligent approach lies in personalized apparel design. The current consumer demand for personalized products continues to grow, the clothing customization market is gradually emerging, and the application of intelligent methods further promotes the development of this trend. By collecting consumers' body data, preferences, wearing habits and other information, smart methods can customize clothing to fit their personal style. This kind of personalized customization service based on big data analysis not only improves consumer satisfaction and loyalty, but also brings new growth points for apparel companies. At the same time, the intelligent method can also provide accurate advice on fabric selection and pattern adjustment to ensure the comfort and aesthetics of customized garments. Nevertheless, the current application of intelligent optimization in the field of apparel design still faces many challenges, including the accurate acquisition of user preferences, the effective combination of creative elements and process requirements, and the match between the final product and the user's expectations, which constrain the efficiency and quality of personalized apparel customization. For this reason, this study proposes a personalized clothing design method based on interactive genetic algorithm, which realizes the efficient combination of creativity and craftsmanship through human-machine collaboration. In this study, we firstly constructed the framework of clothing customization system based on interactive genetic algorithm, binary coded the key elements of clothing such as buttons, collars and pockets as chromosomes, and designed the user interaction interface to enable consumers to intuitively evaluate the clothing solutions. Secondly, the fitness function is applied to transform the user's subjective evaluation into the basis of algorithmic optimization, and the garment design scheme is optimized through cross-variant operation in a continuous iteration. Next, the superiority of the proposed algorithm is verified through comparative experiments, and multiple users are invited to participate in the test to collect and analyze quantitative data. Finally, the advantages and potentials of interactive genetic algorithms in enhancing the efficiency of combining creativity and craftsmanship in personalized apparel design are discussed, and future development directions are envisioned. Through this series of research, it is expected to provide new ideas and methods for personalized clothing customization and promote the in-depth application of intelligent optimization in the field of clothing design.

II. Personalized clothing design based on interactive genetic algorithm

II. A. Genetic algorithms

The basic genetic algorithm [22] can be defined as an 8-tuple:

$$SGA = (C, E, P_0, M, \Phi, \Gamma, \Psi, T) \tag{1}$$

Among them, C - individual coding method, E - individual fitness evaluation function, P_0 - initial population, M - population size, Φ - selection operator, Γ - crossover operator, Ψ - variation operator, T - genetic evolution termination condition.

The flow of the basic genetic algorithm is shown in Figure 1.

II. A. 1) Encoding and decoding

Genetic algorithms can not directly deal with the parameters of the problem space, with genetic algorithms to solve the problem, it is necessary to establish a link between the actual representation of the target problem and the chromosome structure of the genetic algorithm, by the genes according to a certain structure of the chromosome individual to represent the problem solution space, that is, to determine the encoding and decoding process of the gene.

Genetic algorithm application process should first solve the gene coding problem. The current several commonly used coding techniques are binary coding, floating point coding, character coding, integer coding and so on.

Genetic algorithms use binary encoding to represent individual genotypes, which use the usual 0, 1 string generated from the binary-valued character set $\{0,1\}$, to represent candidate solutions in the problem space, so that the actual genotype is a binary string [23]. Its advantages are the simplicity of encoding and decoding operations, the ease of implementation of genetic operations such as crossover and mutation, and the ease of theoretical analysis using pattern theorems, among other things. It is characterized by simplicity, conformity to the principle of minimum character set coding and ease of analysis with the pattern theorem, thus binary value coding is currently the most commonly used coding method in genetic algorithms.

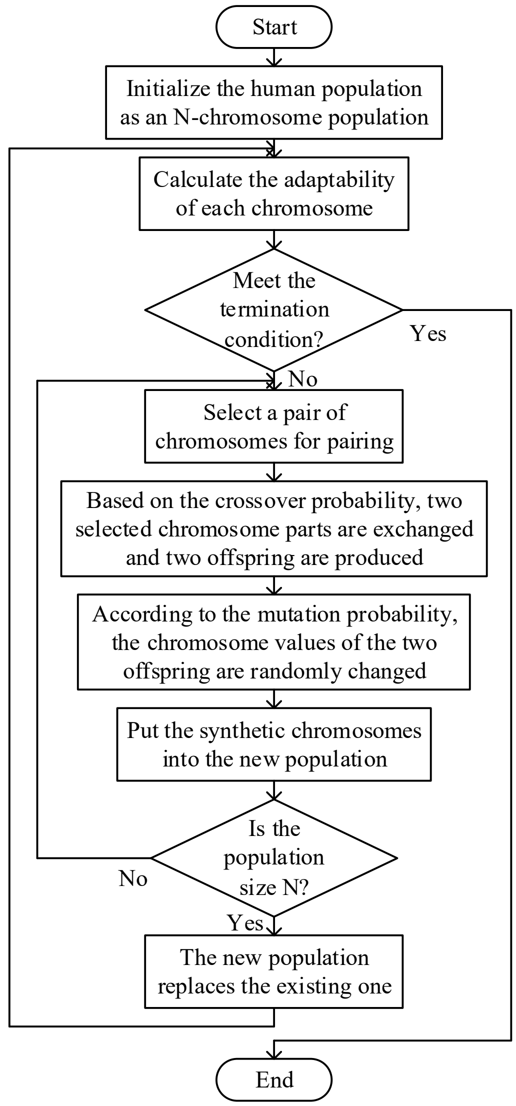

Figure 1: Genetic Algorithm Framework

II. A. 2) Selection of operators

Selection operator is the process of selecting individuals from a population that are better adapted to the environment, the selected individuals will be given the opportunity to retain their genes and reproduce the next generation, so sometimes this operation is also called regeneration. The following selection operators are currently in common use: fitness scaling methods, reproductive pool selection, tournament selection, and linear ranked selection.

Among them, the roulette selection method is the simplest and most commonly used selection method [24].

The method is to first calculate the relative fitness value f_i of an individual according to equation (2), and divide the disk into N parts according to the selection probability $\{p_i, i = 1, 2, ..., N\}$ to divide the disk into N parts, and when making the selection, one can hypothetically rotate the disk, and if a reference point falls into the i th sector, the individual i is selected. This selection strategy can be implemented as follows: first generate a random number within [0, 1], and select individual i if $p_1 + p_2 + \cdots + p_{i-1} < r \le p_1 + p_2 + \cdots + p_i$. The larger the area of the small sector, the higher the probability that a reference point will fall into it, i.e., the larger the adaptation value of an individual, the more chances it will have to be selected. Thus, the greater the probability that its genes will be passed on to the next generation.

Let the size of the population be n and a_i denote the chromosomal individuals, then the population can be expressed as $P=\{a_1,a_2,\cdots,a_n\}$, the fitness of an individual a_i is $F(a_i)$, and the probability of its individual a_i being selected with probability exactly as the share of its fitness value, i.e:

$$p_i=\frac{F(a_i)}{\sum_{i=1}^{n}F(a_i)},i=1,2,...,n \tag{2}$$

II. A. 3) Intersection operators

The crossover operator randomly exchanges certain genes between two individuals in a population selected to participate in evolution with a certain crossover probability, with the expectation of recombining the beneficial genes to produce a new combination of genes. According to the difference of gene coding representation and the difference of crossover position, there can be the following kinds of crossover methods: single-point crossover, multi-point crossover, uniform crossover, etc., among which the most commonly used crossover operator is single-point crossover [25].

The execution process of the specific single-point crossover operator is described below:

(1) Two-by-two random pairings of individuals in a population are made. If the size of the population is M, there are a total of $[M/2]$ groups of individuals paired with each other. Where $[x]$ denotes the largest integer not greater than x.

(2) For each group of individuals paired with each other, the position after a certain locus is randomly set as the point of intersection. If the length of the chromosome is n, there are a total of $n-1$ possible locations for the crossover point.

(3) For each pair of mutually paired individuals, exchange part of the chromosomes of the two individuals at their crossover point with a set crossover probability $p_c(0<p_c\leq 1)$ phase-wise, thus combining into two new individuals.

Crossover can be practiced in the form of single-point crossover or multi-point crossover. For single-point crossover, two randomly selected strings from the crossover pool $s_1=a_{11}a_{12}\cdots a_{1l_1}a_{1l_2}\cdots a_{1L}$ and $s_2=a_{21}a_{22}\cdots a_{2l_1}a_{2l_2}\cdots a_{2L}$, and choosing a randomly selected crossover bit, $x\in[1,2,\cdots,L-1]$, it may be useful to set $l_t\leq x\leq l_2$, the chromosomal bit strings in the right-hand portion of that position in the two bit strings are exchanged, yielding two sub-bit strings individually as:

$$\begin{aligned} s_1^{'}&=a_{11}a_{12}\cdots a_{1l_1}a_{2l_2}\cdots a_{2L},\\ s_2^{'}&=a_{21}a_{22}\cdots a_{2l_1}a_{1l_2}\cdots a_{1L}\end{aligned} \tag{3}$$

II. A. 4) Variational operators

According to the principle of gene mutation in biological inheritance, gene mutation is the process by which individuals in a population selected to participate in evolution randomly select one or more loci in the chromosome coding strings and change the gene values of these selected loci, i.e., perform mutation with a mutation probability p_m on the specific loci of the individual selected to evolve. When representing individual chromosomes in binary code, gene mutation is the inverse of the binary bit in the individual chromosome string where the mutation occurs, if it is a 1 it changes to a 0, if it is a 0 it changes to a 1. The selection of the mutation rate is generally influenced by factors such as population size, chromosome length, etc., and more importantly the probability of mutation p_m selection should be in line with the case of a biological very small mutation so that the probability of mutation can not be taken too large, if the mutation probability is greater than 0.5, then the genetic algorithm will be degraded to a random algorithm, and some of the important characteristics and search ability in the genetic algorithm no longer exist.

II. A. 5) Adaptation evaluation

The fitness function of a genetic algorithm, also called the evaluation function, is an index used to determine the degree of merit of individuals in a population, which is evaluated based on the objective function of the problem being solved [26].

Interactive genetic algorithm is an evolutionary optimization method based on human subjective evaluation as evolving individual fitness, a technique embedded with human preferences, intuition, feelings and psychology, a mapping of feature parameter space to mental space, and a collaborative optimization of the objective by a human and a genetic algorithm [27]. Individual fitness is no longer determined by an explicit evaluation function, but is interactively input by the user based on his or her subjective emotional preferences. Therefore, the individual fitness value is entirely determined by the user, and the user needs to be provided with a reasonable way of inputting the fitness value during the fitness value evaluation process.

II. B. Clothing customization system design

II. B. 1) Coding rule design

In the design of clothing customization system based on interactive genetic algorithm, taking men's suit as an example, the suit as a whole is taken as a chromosome, and each important element in the suit is binary coded separately. In this paper, we take five elements of buttons, collar, pockets, hem, and pattern in men's suit styles to be encoded. For each different clothing element, a different number of binary digits are used to correspond to its code, the specific coding digits are set according to the category of clothing elements, such as button styles (single-breasted, double-breasted) using 1-bit binary coding, and the collar type (flat barge collar, bumpy barge collar, green fruit collar) using a 2-bit binary number coding.

In the customization platform, the user scores the selected clothing styles, and the user scores are sent as input values to the interactive genetic algorithm. The system takes 6 different suit styles as the initial population.

II. B. 2) Crossover and mutation operations

Crossover and mutation operations were performed using the traditional GA scheme. Crossover refers to exchanging certain codes of 2 chromosomes and mutation refers to reversing certain codes of a single chromosome. The crossover schemes used in this paper are single-point crossover, double-point crossover and uniform crossover, and the mutation scheme uses only simple mutations.

In the specific iteration of the algorithm, the 2 genetic operations of crossover and mutation are repeated continuously. Individuals in the new population generated each time will be given to the user for rating to help the algorithm learn user preferences and emotions, so as to gradually select chromosome combinations that are more favorable to user preferences.

II. B. 3) Evaluation of user preferences and adaptability

In the genetic operation process of the clothing customization platform based on interactive genetic algorithm, the fitness function is used as the evaluation basis. The evaluation content is the degree of individual popularity of the style in the clothing population, and at the same time, the evaluation index will be used in the subsequent operation of the system as the basis for genetic evolution. In the process of system implementation, the final score of the function is associated with the establishment of genetic algorithm fitness, and its ultimate goal is to realize the different users' own needs for clothing customization. Therefore, the specific program interaction of the clothing customization platform based on interactive genetic algorithm mainly includes the following steps:

(1) Interpret the binary string code of clothing style styles through decoding algorithm, complete image processing, and finally draw a visualized clothing style map automatically.

(2) The user selects the initialized population according to the system, scores the visualized clothing design scheme shown, and calculates the objective function value of the corresponding clothing style individual. Users only need to score the current garment in the range of 1 to 10 according to their own preferences. All combinations of clothing features (chromosomes) will be searched by the IGA itself to gradually match the user preferences, i.e., the user's emotions and preferences, which do not need to be input by the user from a quantitative point of view, but are guessed by the IGA based on the user's scoring.

(3) Linear fitting of clothing style style objective function values to find the individual fitness.

II. B. 4) Process design

The evaluation process of the clothing customization platform based on interactive genetic algorithm is shown in Figure 2. In this evaluation system, each parameter in the customized clothing is set by the system so as to carry out population initialization, at the same time, in order to satisfy the users who have no target parameter selected to quickly realize the customized clothing collocation, the system generates a variety of classic styles to participate in the population initialization. Users can modify the adaptability of the customization scheme through scoring to make choices for the next generation of genetics. The system generates a new customized clothing scheme through the fitness, and at the same time, the system carries out the cross-mutation operation on the genes in the new population. Repeat the operation, those that do not meet the constraints will be mutated again, and after many rounds of selection and elimination, the system ends the evolution when the user meets the clothing customization scheme.

Clothing populations are initialized, and five different clothing style patterns are used as initialized populations. The user scores the population, the score range is 1 to 10, of which, 1 point represents very dislike, 10 points represents very like, with the increase in the interval with the increase in the score represents the user's favorite clothing styles and patterns. When the user of a child evaluation score of 10 points, on behalf of the user has obtained its favorite clothing style style, the end of the program. When the user evaluation score is between 1 and 10 points, calculate the individual adaptation degree of the clothing style style, and select, crossover, and mutation to generate a new population. Cycle for the user to evaluate, until the output of user-satisfied clothing style styles or to reach the maximum number of iterations set by the system, the program terminates.

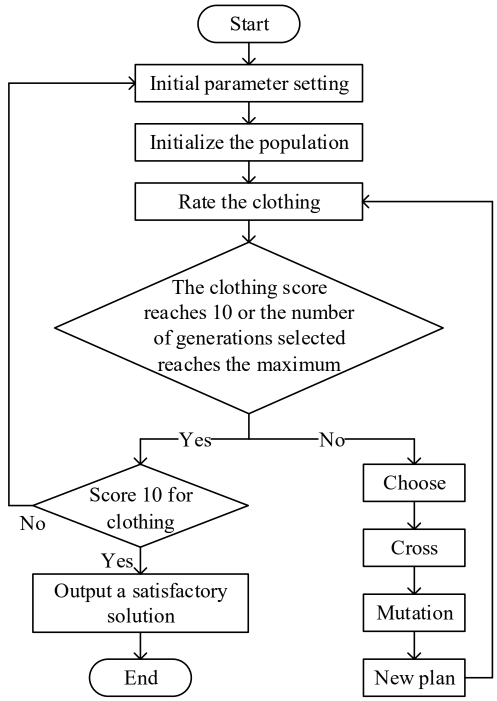

Figure 2: Interactive genetic Algorithm clothing customization process

II. B. 5) Interactive Genetic Algorithm Implementation

The interactive genetic algorithm is denoted as:

$$IGA = (C, E, P_0, M, \Phi, \Gamma, \Psi, T) \tag{4}$$

where, C denotes the coding scheme of the individual. E denotes the individual fitness evaluation function. P_0 denotes the initial population. M denotes the population size. Φ denotes the selection operator. Γ denotes the crossover operator. ψ denotes the variation operator and T denotes the genetic algorithm termination condition. In the algorithm, T is a user-initiated event trigger to terminate the loop.

Let the garment has k components, let x_k be the values taken by the components of the garment, then each garment can be represented by 1 column vector, e.g., the attribute of the pants contains 2 components, pants length and color, so that x_1 and x_2 represent the values taken by the pants length and color, and the 2 values are loaded into 1 vector:

$$X = [x_1, x_2, \cdots, x_k] \tag{5}$$

where, X represents 1 garment generated.
Binary encoding can be used to encode the values of each 1 attribute of the garment in binary:

$$B = BinaryCode(X) \tag{6}$$

where, $BinaryCode$ represents the binary coding operator. B represents the binary sequence generated by X. It can be expressed as:

$$B = [b_1, b_2, \cdots, b_n] \tag{7}$$

P_0 The initial population can be expressed as:

$$P_0 = \{B_1, B_2, \cdots, B_m\} \tag{8}$$

where, m is the number of garments. P_0 represents the 1st generation population generated, containing m garments.

The user scores each 1 garment inside the population out of 10 to get 1 scoring sequence:

$$S = [s_1, s_2, \cdots, s_m] \tag{9}$$

Given that q users have participated in the ratings, q sequences of ratings can be obtained and stored into a matrix of 1 q rows and m columns, which can be expressed as:

$$U = \begin{pmatrix} S_{11} & \cdots & S_{1m} \\ \vdots & & \vdots \\ S_{q1} & \cdots & S_{qn} \end{pmatrix} \tag{10}$$

Find the mean of the user ratings for each 1 garment:

$$\overline{s_j} = \frac{1}{q}\sum_{i=1}^{q} s_{ji} \tag{11}$$

The consensus degree function for clothing is:

$$Consensus(s_j, \overline{s_j}) = 1 - median(| s_{j1} - \overline{s_j} |, \cdots, | s_{jq} - \overline{s_j} |) \tag{12}$$

Define the fitness equation as:

$$Fitness = \omega_1 \overline{s_j} + \omega_2 Consensus(s_j, \overline{s_j}) \tag{13}$$

Where, ω_1, ω_2 is the hyperparameter, an empirically defined weighting parameter.

III. Experimental analysis

III. A. Algorithm Validation Analysis

The initial number of populations selected for the experiment is 8 groups, and the selection of parts is based on a single-point crossover mode, with the initial crossover probability p_c and the initial mutation probability p_m taking the values of 0.6 and 0.8, respectively, and the iterative operation using this paper's genetic algorithm is carried out, and the results converge at the 10th iteration, so that the results are outputted, and 10 users can According to their own preferences, combined with the degree of importance of the components of each clothing style rating, the genetic algorithm according to the user's evaluation index constantly optimize the population. The initial population of the system is randomly generated from each style part, the population number represents the evaluation order of the user, and the part number represents the order of the style parts in the style library, and the composition of the initial population is shown in Table 1.

Table 1: Initial population composition

Population number	Sleeve parts	Collar unit	Garment parts	Sleeve texture	Collar texture	Body texture
1	13	13	8	T060	T062	T066
2	16	8	14	T065	T063	T005
3	17	8	4	T032	T007	T076
4	13	9	9	T007	T063	T023
5	14	4	12	T073	T045	T009
6	15	4	12	T052	T076	T008
7	14	13	10	T003	T031	T016
8	11	15	13	T012	T031	T003

The population converged at the 10th generation of evolution and the composition of the evolved population is shown in Table 2.

Table 2: Evolutionary population composition

Population number	Sleeve parts	Collar unit	Garment parts	Sleeve texture	Collar texture	Body texture
1	10	11	4	T003	T023	T012
2	12	6	11	T045	T066	T001
3	14	8	2	T008	T001	T003
4	10	7	6	T006	T003	T063
5	10	2	11	T063	T053	T061
6	11	3	10	T073	T061	T001
7	10	11	9	T023	T063	T003
8	6	11	12	T006	T031	T006

Comparing Table 1 and Table 2, at the initial stage of the population, the system forms multiple combinations of style components according to the existing style component library, when the user scores each style according to personal preference, the interactive genetic algorithm evolves according to the scoring aesthetics, and when it reaches the 10th generation of the population, the clothing styles gradually converge to the user's preference.

In order to verify the effect of interactive genetic algorithm clothing style optimization, this paper chooses two-dimensional tailoring method (Method 1), particle swarm method (Method 2), simulated annealing method (Method 3), the traditional genetic algorithm (GA) and the interactive genetic algorithm (IGA) for example comparison, and the results are shown in Figure 3. As the number of interaction generations increases, the aesthetics value increases, and when the number of interaction generations is the same, the interactive genetic algorithm proposed in this paper can obtain higher aesthetics value than the traditional genetic algorithm and the 2D cropping method, with an average improvement ratio of 18.32% and 35.06%, respectively, so as to achieve the user's satisfaction results quickly through the evolution of interaction.

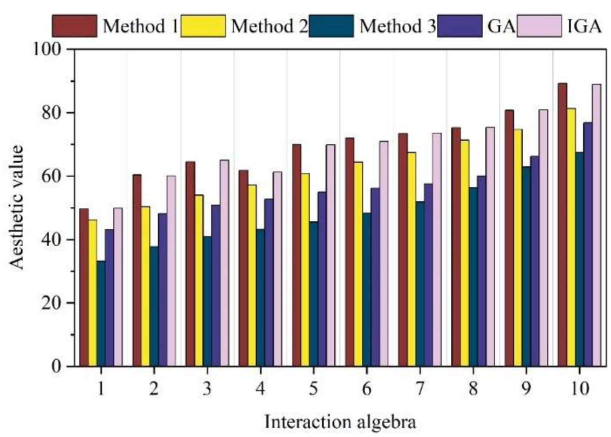

Figure 3: Example comparison of five methods

III. B. Analysis of the efficiency of combining creativity and craftsmanship

This chapter validates the efficiency of a garment customization system for combining creativity and craftsmanship using a plaid color fabric pattern. Initially, the system generates the initial population of the pattern based on the formulated color matching principle and the chromosome construction code of the plaid-type color fabric pattern. Then, the plaid pattern effect is shown to the user in the form of pattern on the interface, and the adaptation value of the individual population is obtained through the user's evaluation scoring.

Twenty users are invited to conduct the experiment. In this experiment, the crossover and variance probabilities were set to 0.6 and 0.8, respectively. The termination condition of the algorithm is whether 6 satisfactory tattoos have been acquired or whether the number of evolutionary generations has reached 10.

The average fitness values and the best fitness values for 20 users when obtaining 6 satisfactory patterns are shown in Fig. 4. The mean adaptation values for all six satisfaction patterns for the 20 users were greater than 88.67, with the highest mean adaptation value reaching 91.96. The optimal fitness values were all over 89 and even up to 97.

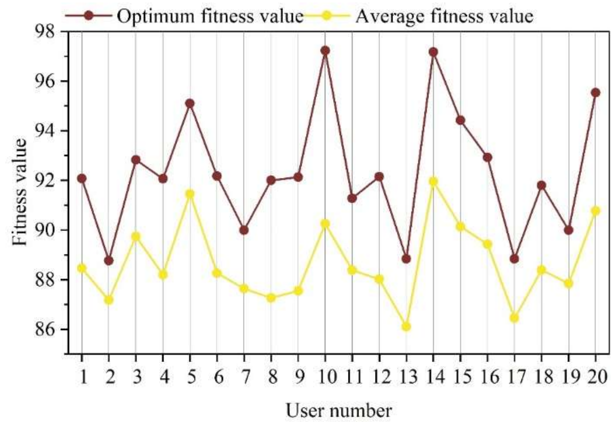

Figure 4: The average fitness value and optimum fitness value of the satisfied dress

The corresponding evolutionary generations are shown in Figure 5. The evolution time for different users to obtain satisfactory patterns varies from person to person, but the range of evolutionary generations for all users is between 4 and 8. The test results indicate that the pattern optimization design system is able to evolve user-satisfactory checkerboard type color weaves in fewer generations.

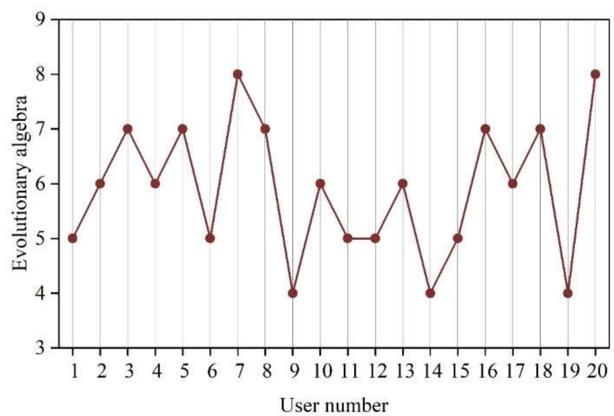

Figure 5: User evolution algebra

Taking user No. 20 as an example, the average fitness value and the best fitness value recorded by the system for this user during the evolutionary process are shown in Fig. 6. Although there are some small fluctuations, overall the user's average fitness value in the evolutionary process is increasing with the trend of the best fitness value, indicating that with the increase of the number of interactive evolutionary generations, the user's satisfaction is also gradually increasing.

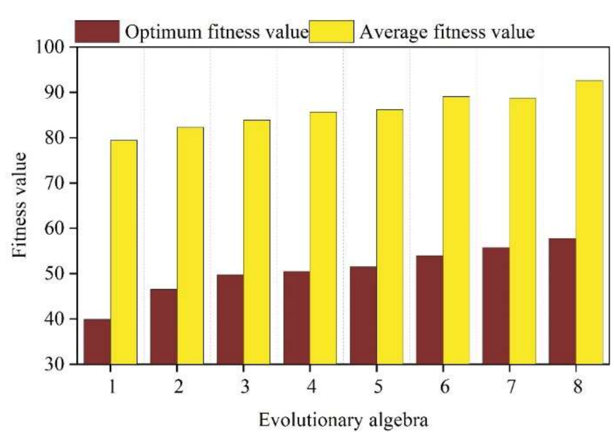

Figure 6: The average fitness value is compared to the optimum fitness value

III. C. Comparative analysis of user satisfaction

Ten users were selected to evaluate the design solutions based on traditional genetic algorithm (GA) and interactive genetic algorithm (IGA) respectively. The statistical mean values of the evaluation maxima per generation are shown in Fig. 7. It can be clearly observed that the mean value of the evaluation maximum per generation of IGA is higher than that of GA in the initial population selection, IGA evolves to reach the evaluation maximum in the 10th generation, and the average number of generations of convergence in which all the testers reach satisfaction is the 9th generation, which is high relative to GA.

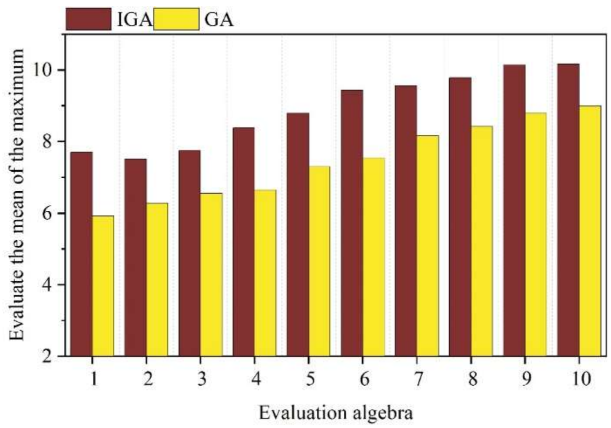

Figure 7: The test staff evaluates the mean of the maximum per generation

The 10 users typical and atypical get satisfied solution evaluation convergence algebra is shown in Fig. 8. The number of generations evaluated by users in IGA is less than that of GA algorithm, and the slowest evolution in IGA reaches convergence in 10th generation, and the fastest generation is the 4th generation to get the user's satisfactory solution. In GA, the user's satisfactory solution can be obtained in the 5th generation at the earliest, but the evolution reaches convergence in the 12th generation at the latest. Obviously IGA can reach user satisfaction more easily than GA, which is due to the fact that the initial clothing style is not fixed in GA and the system is not given any indication, resulting in a random initial population produced in each run. The experimental results show that the IGA algorithm is not only effective in relieving the user's fatigue, but also enhances the user's cognition of the system, and since the initial population is much less complex, the user can effectively obtain an efficient and accurate cognition of the population, which reflects the good convergence of the proposed IGA and the design of the garments is more satisfying to the user.

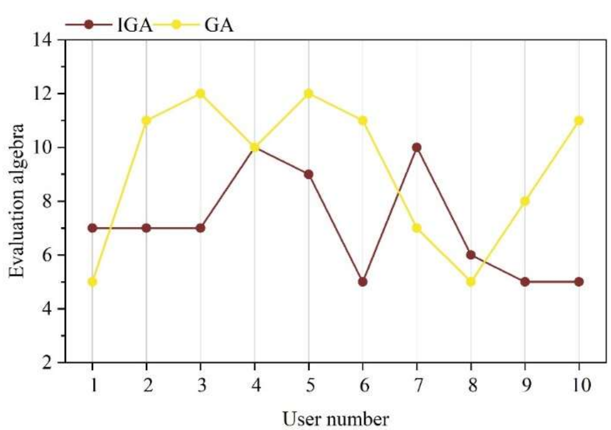

Figure 8: The user is satisfied with the evaluation convergence algebra

IV. Conclusion

The personalized clothing design method based on interactive genetic algorithm realizes the efficient combination of creativity and craftsmanship through the human-computer collaborative design mode. Experimental results prove that this method has significant advantages in obtaining user-satisfied design solutions compared with traditional methods. Comparative experiments show that the interactive genetic algorithm improves the aesthetics by 18.32%

and 35.06% over the traditional genetic algorithm and the 2D cutting method, respectively, when obtaining the same user evaluation. In the validation experiments for the checkered color fabric pattern, the average fitness value of the six satisfactory patterns obtained by 20 users is greater than 88.67, and the highest fitness value reaches 97, and all the users can obtain a satisfactory design solution within 4-8 generations, which significantly shortens the design cycle. Compared with the traditional genetic algorithm, which needs 12 generations to reach convergence at the latest, the interactive genetic algorithm needs only 10 generations to obtain a satisfactory design, which is a significant improvement in efficiency. This high efficiency stems from the fact that the interactive genetic algorithm can accurately capture user preferences and quickly adjust the optimization direction, avoiding the inefficiency caused by blind search. It is also found that the interactive genetic algorithm can not only effectively alleviate user fatigue, but also enhance the user's cognition of the system. Due to the small initial population complexity, the user can efficiently and accurately cognize the characteristics of the population, reflecting the good convergence of the proposed algorithm. The successful application of this method provides a new idea for personalized clothing design and will have a positive impact on the development of the clothing customization market.

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