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User Preference Adaptive Fitness of Interactive Genetic Algorithm Based Ceramic Disk Pattern Generation Method

HUAFEI CAI 

School of Art and Design, Guangdong University of Finance and Economics, Guangzhou 510320, China

Corresponding author: Huafei Cai (caihuafei2010@163.com)

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ABSTRACT Pattern design in real life is a complex optimization challenge that objective function can not express explicitly, and can be classified as an implicit target optimization problem. Owing to the fact that the objective function in implicit target optimization problem can not be completely structured, the traditional intelligent decision optimization method is inapplicable. This paper proposes an interactive genetic algorithm based on user preference adaptive fitness, in which users actively participate in optimization and take their subjective evaluation value as the adaptive fitness of evolutionary individuals. On the basis of adjusting the tone coordination degree of ceramic disc pattern, the improved method gives the calculation of user interest degree and style similarity, and completes the establishment of user preference model. The individual similarity calculation of the algorithm integrates the user preference information, making the calculation result more objective. In the experiment, the grain genes of ceramic disc pattern can be divided into two types: main body and border, both of which can be encoded by 16-bit binary code strings. And the weight values of style, tone collocation and structure were set respectively, and the ceramic disc patterns of modern fashion and fresh styles were obtained. In addition, the algorithm performance comparison is also completed. The experimental results show that with the progress of evolution, the midpoint and average width of the fitness of the population decrease, and the population quality is improved. Our algorithm can generate ceramic disc patterns of different styles, and the algorithm can obtain more satisfactory solutions in less evolutionary generations, which speeds up the algorithm's convergence speed and shows better evolutionary optimization ability.


INDEX TERMS Interactive genetic algorithm, user preferences, fitness, ceramic, design of disc.

I. INTRODUCTION

In today's society, with the improvement of living standards, people's consumption concept is gradually changing. In the process of purchasing commodities, consumers not only pay attention to the practicality of commodities, but also attach increasing importance to the appearance and artistic modeling of commodities [1]. The artistry of the goods imperceptibly improves the taste of the customers in choosing the goods, and also improves the value of the goods in the minds of the customers. The most part of the work in the artistic design is pattern design. The traditional pattern design process is first conceived in the mind of the designer and then expressed through paper and pen. Not only are the quality and

quantity of traditional designs limited by human imagination, the subsequent modification process is also troublesome. Therefore, it becomes the bottleneck of product design, and it is difficult to satisfy people's higher desire for novelty, beauty and comfort.

Interactive genetic algorithm (IGA) is a feasible method to solve optimization problems that are difficult to be expressed by well-defined functions [2]. This method can combine the traditional evolutionary mechanism with the user's intelligence evaluation, and directly obtain the fitness of the evolving individual through human-computer interaction, instead of the fitness function which is difficult to express clearly. At present, this algorithm has been successfully applied to face recognition, costume design, music creation, speech processing, music retrieval, robot vision and other fields. In comparison with the traditional genetic algorithm (GA) [3], [4],

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the most significant characteristic of the interactive genetic algorithm is the adaptive fitness of users' evaluation of evolving individuals. Since the individual fitness is generated by the customer evaluation, the fitness [5], [6] can reflect the customer's subjective preference. In addition, the customer's preference will make the fitness uncertain. However, as the uncertainty increases, the accuracy of fitness will decrease and the effect of evolutionary optimization will become worse. Therefore, the direct way to improve the accuracy of fitness and reduce uncertainty is to pay more attention to the evaluation of individuals, which will undoubtedly cause fatigue and increase the uncertainty of evaluation. However, improving the accuracy of fitness and reducing the operation burden are contradictory to each other, which is also a research point of interactive genetic algorithm [7].

At present, there are roughly two ways to solve this problem: (1) By establishing a reasonable fitness assignment, some IGA-based methods can improve the man-machine interaction environment, reduce the operating burden and improve the accuracy of adaptive fitness; (2) On the basis of the evaluation characteristics, the uncertainty of individual fitness is extracted, and an appropriate agent model is adopted to estimate the fitness of evolving individual and reduce fatigue.

Many scientists research the first class of methods to improve interactive genetic algorithm. Raghuwanshi proposed a large population interactive genetic algorithm based on implicit feedback and explicit feedback [8]. Although this method can enhance the search ability without increasing user fatigue, the values of key parameters in the algorithm need to be given in advance, which will greatly affect the performance of the algorithm. Gong *et al.* [9] brought up an improved interactive evolutionary algorithm that interacts with the decision-maker to obtain the optimal solution. According to whether the individual similarity is greater than the set classification threshold, Kim and Kim [10] classified the population. This method does not need to set up the classification number in advance, which can change dynamically with the evolution process. However, in this algorithm, the classification similarity threshold needs to be set in advance, and the constant similarity threshold will have a significant impact on the performance of the algorithm. In method [11], a discrete adaptive fitness assignment method was proposed, which reduced the operation burden to some extent. However, the accuracy of the discrete adaptive fitness itself was poor, and this method did not take the uncertainty of the evaluation into consideration. In methods [12]–[14], adaptive fitness assignment methods based on interval and fuzzy numbers are proposed. Compared with precise and discrete numbers, interval and fuzzy numbers can better reflect the uncertainty and progressiveness of the evaluation process, and greatly improve the accuracy of adaptive fitness. However, in the operation of adaptive fitness assignment, the interval number should be evaluated twice by the upper and lower limits, and the fuzzy number should be determined by the center value

and width, which actually increase the burden of operation. Similar problems still exist in method [15].

Besides, a number of scientists have been working on the second class of methods to improve interactive genetic algorithm. On the basis of machine learning technology, a variety of interactive genetic algorithms were proposed [14], [16], [17] to predict the evaluation results by proxy model, which could reduce some of the heavy evaluation work. Machine learning technologies expand search capability, reduce operation burden and improve algorithm performance. However, these proxy models are based on different adaptive fitness assignment methods to extract valuable information and are inevitably affected by information loss. Manfre *et al.* [18] proposed a co-interactive evolutionary optimization method to accelerate the current population evolution process by using other population evolution results, but this method did not consider the impact of individual similarity on collaborative interaction. In Methods [19]–[21], multi-user collaborative based interactive genetic algorithms were proposed. Current users can browse and add other user ratings online, while these methods are limited by the number of collaborative users and the size of the user base. Darani and Kaedi [22] used evaluation information from other users as training samples to reduce user fatigue and estimate individual fitness. Although the introduction of agent model is helpful to improve group decision-making, users cannot directly exchange information, which limits the further improvement of collaboration quality. Besides, some scholars [23]–[27] combined swarm intelligence algorithm to solve the contradiction between improving the accuracy of adaptive value and reducing the burden of operation. Using two different evolutionary learning strategies, namely differential evolutionary flame generation and dynamic flame guidance, Li *et al.* [27] designed a double-evolutionary learning algorithm for generating high-performance flame and dynamically guided moth search.

In view of the above shortcomings, this paper studies how to improve the performance of the algorithm under the premise of reducing user fatigue with adoption of large-scale population evolution, and proposes a improved interactive genetic algorithm based on user preference adaptation value. The advantage of this method is that the individual similarity calculation integrates the user's preference information, which makes the calculation result more objective. The selected individuals for user evaluation are evenly distributed in the contemporary population, which further reduces the burden of evaluation. In addition, the fitness estimation based on the user preference model makes use of all the individual information of the user evaluation. Besides, our method takes into account the weight of each component and the influence of combination preference, and adopts the fitness estimation formula of evolutionary individuals to make the estimation result more accurate.

The innovation points of this paper are as follows: (1) The disk pattern is divided into two types of grain genes: main and border genes, both of which are encoded by 16-bit binary

code strings. The ceramic disk patterns of different styles can be generated by setting the style, tone collocation and structure weight respectively; (2) Individual similarity calculation integrates user preference information to make the calculation results more objective; (3) The selection of individuals for user evaluation has a uniform distribution in the contemporary population, which further reduces the burden of the algorithm; (4) In evaluating the fitness of individuals not assessed by the user, our method takes into account the weight of each component and the effect of component combination preferences. In addition, the fitness estimation formula of evolutionary individuals is put forward to make the calculation result more accurate.

II. THEORETICAL FOUNDATION

There are some optimization problems in industrial design, artistic design, product design and other fields. The optimization goal is generally to “meet a certain demand of people”, and the optimization objective function is often difficult to quantify and needs to consider user preference and emotion. Such problems are called the implicit target optimization problem. Interactive genetic algorithm is one of the effective methods to solve the implicit target optimization problem. On the basis of the interactive genetic algorithm, this paper proposed a user preference adaptive fitness of interactive genetic algorithm to solve this problem and generate ceramic disk patterns with different style, tonal collocation and structure.

A. TRADITIONAL GENETIC ALGORITHMS

(1) Genetic algorithm (GA) [28] is a computational model of biological evolution based on natural selection and Darwin’s genetic mechanism of biological evolution, which simulates reproduction, hybridization and mutation in natural selection and genetic process. Because of the complexity of engineering to mimic gene coding, the researchers simplified the coding according to the actual situation of the research target. In each generation, new populations can be generated based on the fitness of individuals in the problem domain. Owing to the fact that the new generation of individuals inherited some of the good traits of the previous generation, the performance is better than the previous generation, and gradually towards the direction of the optimal solution evolution. With the increase of algebra, the optimal individuals in the last population can be decoded as the approximate optimal solution of the problem. The process of the traditional genetic algorithm is shown in figure 1.

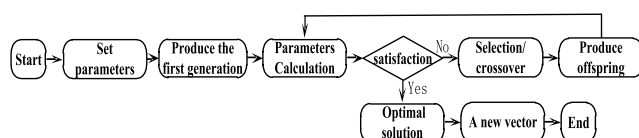


FIGURE 1. The process of the traditional genetic algorithm.

The essence of genetic algorithm is to search continuously and randomly in space to generate new solutions and retain

better ones. In this paper, an improved genetic algorithm is adopted to simulate the evolutionary process [29] of a population (i.e. ceramic disc pattern design), and then satisfactory ceramic disc patterns are designed. In this process, it can be thought that the genes make up the ceramic disk pattern; A ceramic disk pattern consists of multiple genes; A population consists of multiple individuals (ceramic disks patterns); The fitness function determines the quality of each individual.

B. INTERACTIVE GENETIC ALGORITHM

The interactive genetic algorithm combines the traditional evolutionary mechanism with the user’s intelligent evaluation. This method implements the evolutionary operation based on the fitness of the evolutionary individual given by the user, and replaces the fitness evaluation on the basis of the mathematical model. Therefore, it is a feasible method to generate ceramic disk patterns.

The program can generate n individuals randomly according to the encoding, and present each ceramic disk pattern on the interactive interface after decoding. This process mimics the DNA translation in biology, that is, the process of mapping genotypes to phenotypes. To facilitate user selection, the initial population generated by the algorithm is n ceramic disk patterns. Then, users can choose the individuals on the basis of their own preferences. This process passes on the genes of the individuals they prefer to the next generation, and those that are not selected are weeded out, as are the genes of mutated individuals. After that, the algorithm carries on the evolution operation according to the score result, generates a series of schemes for users to choose. Users can interact with the program to continuously generate a new generation of ceramic disk patterns.

The program records the user’s choice in the background and captures the user’s preference. The genotype of the selected ceramic disk patterns are added to the list, and the last digit of the list is fitness [30]. The initial fitness is set to 1, which increases with the increase of algebra, and if users select the phenotype that has been chose previously, the fitness of the corresponding genotype in the list is increased by 1 and replaced with the new value. Compared with traditional genetic algorithms, interactive genetic algorithms can code users preferences by scoring them. Adaptive evaluation of user deep engagement is not only a special feature of interactive genetic algorithm, but also a joint point of its application to the field of art design. These characteristics can be used to deal with fuzzy evaluation index on the basis of users’ preferences and emotion. The process of the interactive genetic algorithm is shown in figure 2.

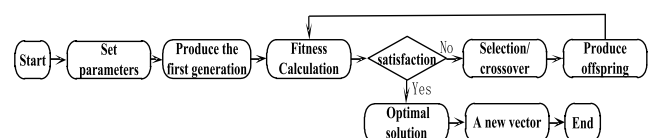


FIGURE 2. The process of the interactive genetic algorithm.

The basic process is as follows:

(2) Initialize the population; (2) Users make the first filter based on personal preference; (3) Calculate the fitness of each individual in the population; (4) Complete selection of individuals, recombination, mutation and other operations; (5) Repeat steps (2) and (3) until the stop rule is satisfied.

C. UNCERTAINTY OF ADAPTIVE FITNESS

Without loss of generality, there are problems to be considered for optimization. And these problems are called the implicit target optimization problem, can be depicted by Eq.(1) and Eq.(2),

$$\max F(x) = \max F\{x_1, x_2, \dots, x_n\} \quad i \in n \quad x_i \in g_i \quad (1)$$

$$g_i = \{x_{i1}, x_{i2}, \dots, x_{im}\} \quad S = \bigcup_{i=1}^n g_i \quad (2)$$

where, x_i is the i th attribute variable, with a total of n attributes. G_i means the domain of x_i , g_i the set containing $m \times i$ elements, and m number of users who participated in the rating, S denotes the domain of the problem to be optimized, $F(x)$ is the optimal combination of attributes given by users according to their cognition and preference.

III. OUR METHOD

A. TONAL COORDINATION ADJUSTMENT OF CERAMIC DISC PATTERN

A ceramic disc pattern is composed of two parts: main gene and border gene. Whether the two genes are compatible or not, an important criterion is the tonal coordination of each gene [31]. In this paper, mutual information on the basis of color histogram is used to characterize tonal coordination. In Eq.(3), A and B represent the main pattern gene and the border pattern gene respectively, and CH_A and CH_B the color histogram of the two genes separately. And the tonal coordination of two genes w can be defined as Eq.(3),

$$w = MI(CH_A, CH_B) \quad (3)$$

where, $MI(CH_A, CH_B)$ is the mutual information of A and B , and its calculation formula can be expressed as:

$$MI(CH_A, CH_B) = H(CH_A) + H(CH_B) - H(CH_A, CH_B) \quad (4)$$

where, $H(CH_A)$ and $H(CH_B)$ are the information entropy of variables CH_A and CH_B respectively, and $H(CH_A, CH_B)$ is the joint information entropy of CH_A and CH_B . And if the tonal coordination of the three genes are higher, the disk patterns are better.

B. INTERACTIVE GENETIC ALGORITHM ON THE BASIS OF USER PREFERENCE ADAPTIVE FITNESS

1) USERS' INTERESTINGNESS

A complete ceramic disc pattern consists of two genes, the main pattern gene and the border pattern gene. Accordingly, we can generate ceramic disc patterns randomly according to the corresponding coding rules. By using the user's score to evaluate whether the disc pattern can be

passed on to the next generation, then we can calculate the fitness of the individual according to the calculation rules, and repeat the above processes. Then by decoding the evolution of individuals, we can get multiple ceramic disc patterns, i.e., a population. On the basis of researching change regularity of user interest [32], this paper took the browsing time of different ceramic disc patterns as the measurement index and quantified users' interestingness [33], [34] by Logistic model. Suppose the evaluation time of the current user u to individual x_i is $T_{ua}(x_i)$, then the interestingness of user u to individual x_i is denoted as Eq.(5).

$$In_u(x_i) = \frac{1}{1 + e^{-(\xi + \eta \cdot T_{ua}(x_i))}} \quad (5)$$

ξ and η are parameters related to the optimization objective, which can be fitted by experiments.

2) CALCULATION OF STYLE SIMILARITY

The i th individual in the population is denoted as x_i , and the phenotype of x_i can be expressed as Eq.(6),

$$x_i = \{x_{i1}, x_{i2}, \dots, x_{ig}\} \quad x_i \in \{l_1^\gamma, l_2^\gamma, \dots, l_g^\gamma\}, \quad \gamma \in [1, g] \quad (6)$$

where, γ mean the attributes that make up an individual, $l_1^\gamma, l_2^\gamma, \dots, l_g^\gamma$ are the attribute value of $x_{i\gamma}$. Assume that x_j is the reference individual evaluated by user u , x_j can be defined as Eq.(7),

$$x_j = \{x_{j1}, x_{j2}, \dots, x_{jg}\} \quad x_j \in \{l_1^\gamma, l_2^\gamma, \dots, l_g^\gamma\}, \quad \gamma \in [1, g] \quad (7)$$

where, γ mean the attributes that make up an individual, $l_1^\gamma, l_2^\gamma, \dots, l_g^\gamma$ are the attribute value of $x_{j\gamma}$. Based on cognitive fuzziness, Gaussian function can be used to describe the attribute similarity relationship between individual x_i and x_j , as can be seen in Eq.(8).

$$u(x_i) = e^{-\left(\frac{x_{i\gamma} - x_{j\gamma}}{In_u(x_{j\gamma})}\right)^2} \quad (8)$$

Then we calculate the average value of attribute similarity between individual x_i and x_j , as shown in Eq.(9).

$$u(x_i, x_j) = \sum_{\gamma=1}^g \frac{u(x_i)}{g} \quad (9)$$

$u(x_i, x_j)$ is non-dual, and the larger the value, the stronger the individual similarity.

3) RECOMMENDATIONS OF USERS EVALUATION RESULTS

The individual with the highest user evaluation result of generation $t - 1$ is set as x_B . On the basis of formula (10), the similarity between x_i and x_B of the current generation t can be calculated. In descending order of similarity, select the first N_C of g individuals and recommend them as satisfied ones.

$$u_a(x_i, x_B) = \sum_{\gamma=1}^{N_C} \frac{u(x_i)}{g} \quad (10)$$

The process of transforming the subjective evaluation into quantitative results is as follows: firstly, the subjective factor

K is decomposed into several sub-factors, namely $K = \{k_1, k_2, \dots, k_n\}$, where, n is the number of sub-factors. Design weights for each subfactor, and set the weights as $W = \{w_1, w_2, \dots, w_n\}$, which satisfies the following formula (11).

$$\sum_{i=1}^n w_i = 1 \quad w_i \in [0, 1] \quad (11)$$

For any automatically generated ceramic disc pattern, suppose the score set is $S = \{s_1, s_2, \dots, s_n\}$, s_i is the score of sub-factor K_i . Then, the final score of this ceramic disc pattern can be denoted as formula (12).

$$score = \sum_{i=1}^n w_i \cdot s_i \quad (12)$$

In order to further reduce the influence of subjective factors [35], this paper presents a method of scoring automatically generated ceramic disc patterns by multiple people simultaneously. According to the professional level of participants, they are divided into expert level and ordinary level. Assume that the number of participants is m , $score_i$ is the evaluation result of the participant i , α_i the weight of $score_i$. If the participant i is expert, $score_i = 1$; otherwise, $score_i = 0$. Then the overall score of the ceramic disc pattern is designed as follows:

$$score = \frac{\sum_{i=1}^m \alpha_i \cdot score_i}{\sum_{i=1}^m \alpha_i} \quad (13)$$

C. ESTABLISHMENT OF USER PREFERENCE MODEL

User preference is defined as the rational choice made by people for products or services. It is the comprehensive result of the tradeoff between users' cognition and psychological feelings. The user preference model is a nonlinear mapping from the subjective psychological space to the objective feature space. The user preference model M can be defined as a binary group, denoted as $M = (I, F)$. Where, I is a matrix, and each row of I represents the genotype information of an evolutionary individual in the population. and F is a column vector, representing the adaptive fitness of the corresponding evolutionary individual in I . The user preference model M is expressed as follows:

$$M = \begin{pmatrix} a_{11} & \dots & a_{1y} \\ \dots & \dots & \dots \\ a_{d1} & \dots & a_{dy} \end{pmatrix} \begin{pmatrix} f_1 \\ \dots \\ f_d \end{pmatrix} \quad (14)$$

where, a_{ij} represents a local gene segment that can only express a certain function, that is, the gene coding corresponding to a certain phenotype of an evolving individual. f_i represents the fitness of evolved individuals ($a_{i1}, a_{i2}, \dots, a_{iy}$). Where, d represents the number of evolutionary individuals in the user preference model, y the number of components of evolutionary individuals, $i = 1, 2, \dots, d; j = 1, 2, \dots, y$.

D. ADAPTIVE FITNESS ESTIMATION BASED ON USER PREFERENCE MODEL

In genetic algorithm, the fitness is used to measure the degree to which evolutionary individuals in a population can find the most satisfactory solution in the optimization process. And the individuals with higher fitness are more likely to inherit to the next generation. In the process of user interaction of our method, the fitness is directly assigned to evolutionary individuals, that is, fitness of the evolutionary individual represents the degree of user preference. However, under the constraint of human fatigue, the user preference model proposed in this paper can be used to evaluate individuals, and the most satisfactory solution can be found in a large solution space as soon as possible.

In order to reflect the user preference, this paper establishes the historical evaluation data of the user preference model to select the individual information whose fitness is higher than the average, that is, the individuals whose fitness is higher than the average of the evolutionary individuals evaluated by the user are called preferred individuals. Combined with the above concepts, the calculation formula of component preference value $f(e_{ij})$ is as follows:

$$f(e_{ij}) = \sum_{i=1}^v \frac{f_i p_j}{l} = \frac{1}{l} \sum_{i=1}^v f_i p_j \quad (15)$$

where, l represents the total number of preference individuals that have been evaluated by users, e_{ij} a type of style favored by users, v the number of preferred individuals in e_{ij} that have been evaluated by users, f_i the individual fitness of preference e_{ij} that has been evaluated by users, and p_j the weight of components corresponding to e_{ij} , as shown in Eq.(16).

$$\sum_{j=1}^v p_j = 1 \quad (16)$$

In consideration of the relation between the constituent parts of evolutionary individuals, the definition of preference combination is given in this paper. That is, in the process of evolution, when the occurrence frequency of component combinations exceeds a certain threshold value α , such component combinations are called preference combinations. In the stage of fitness estimation, the fitness of evolutionary individuals with preference combinations should be correspondingly increased, and the preference combination coefficient λ should be introduced. λ depends not only on the frequency of composition $Freq$, but also on the number of composition components $Count$. That is, the more frequently a preference combination occurs and the more components it contains, the bigger λ is. As can be seen in Eq.(17).

$$\lambda = \frac{Freq}{l} \times \frac{Count}{v} \quad Freq = 1, 2, \dots, l; \quad Count = 2, 3, \dots, v - 1 \quad (17)$$

Based on the combination of the fitness of each component and the relationship between the components, the adaptive

fitness estimation model of evolved individual x_o is provided in Eq.(18).

$$f(x_o) = \begin{cases} (1 + \lambda) \sum_{j=1}^y f(e_{ij}) & \alpha \geq \alpha_c \\ \sum_{j=1}^y f(e_{ij}) & \alpha < \alpha_c \end{cases} \quad (18)$$

In formula (17), x_o denotes any newly evolved individual in our method, and α_c the specific threshold.

To sum up, the user preference model in our method is based on the adaptive fitness of each independent component. And for the purpose of protecting the dominant gene from being destroyed, the individuals with the highest fitness value in each generation will be retained directly to the next generation. The process of our method is shown in figure 3.

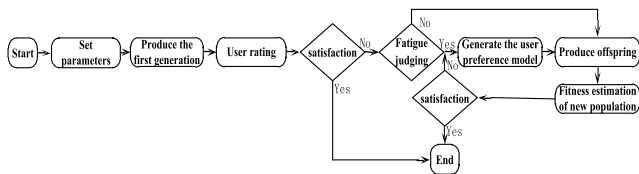


FIGURE 3. The process of our method.

The basic process is as follows:

(1) Set relevant parameters. (including population size, total number of users, crossover mutation probability, threshold α_c , etc.); (2) Evolutionary individuals are generated by random method to form the initial population; (3) Decoding: users evaluate the evolution of individual phenotype, and the fitness can be obtained through the user score in our algorithm; (4) Satisfaction judgment: if users are satisfied with the contemporary optimal individual, then go to step 10; otherwise, go to step 5; (5) Fatigue judgment: if users feel tired, go to step 7; otherwise, go to step 6; (6) Using evolutionary operation to generate a new generation of population, then turn to step 3; (7) According to the individual preference information, the machine learning is carried out to construct the user preference model; (8) A new generation of population is generated by genetic evolution operation. And for the new individuals generated by genetic manipulation, the fitness of individuals can be calculated by formula (17), and the individual with the highest fitness of the new population is presented to the user as the optimal individual of the current generation; (9) Satisfaction judgment: if users are satisfied with the contemporary optimal individual, then go to step 10; otherwise, go to step 7; (10) Finally, the most satisfactory solution is presented to the user, and population evolution algebra, user evaluation times and other statistical information are stored.

IV. EXPERIMENTAL COMPARISON AND ANALYSIS

A. PARAMETER SETTING

The development environment of this paper is Matlab 7.6.0. Considering the needs of man-machine interaction [36], users are required to automatically score the generated ceramic disk

patterns, so the GUI mechanism of Matlab is used [37]. In this paper, ceramic disk patterns are selected and disassembled into parameters understandable by the computer. Then our algorithm is adopted to generate ceramic disk patterns. Moreover, rules and fitness are established to determine the extent to which users involvement affected genetic changes.

In order to verify the effectiveness of the method in this paper, our method is compared with three state-of-the-art methods [11], [14], [20]. In our method and other three comparison methods, the population size N is 150, the maximum evolutionary number T 20. And crossover and mutation probability are 0.6 and 0.01, the minimum and maximum values of the adaptive fitness 0 and 100, respectively. Besides, in our method, preference combination coefficient λ and the total number of users m are 20% and 20, ξ and η 7.363 and 0.986, separately.

B. CODING OF CERAMIC DISK PATTERNS

The ceramic disk pattern is composed of two types of grain genes, main gene and border gene, and is encoded by a 16-bit binary code string. Where the first 8 bits represent the style of the main gene, and 9 to 18 bits the style of the border gene. If represented in decimal, there are 256 sets of body and border styles, ranging from 0 to 255 integers. Users are required to choose a satisfactory design from 65536 candidate ceramic disk patterns according to their preferences. In this process, it can be thought that the genes make up the ceramic disk pattern; A ceramic disk pattern consists of two genes; A population consists of multiple individuals (patterns of ceramic disks); The fitness function determines the quality of each individual. Fig.4 and Fig.5 are examples of main genes and border genes, respectively.



FIGURE 4. Examples of main genes.

C. GENERATION OF CERAMIC DISK PATTERNS

The subjective scoring factor F can be divided into three categories, style, tonal collocation and structure. It can increase



FIGURE 5. Examples of border genes.

the weight of the corresponding factors to produce a certain style of pattern. For example, to generate a certain style of disk pattern, it can set the weight of the style to 0.6, and the weights of tone collocation and structure to 0.2, respectively. This paper takes the generated modern fashion style and fresh style as an example, as shown in Fig.6 and Fig.7.

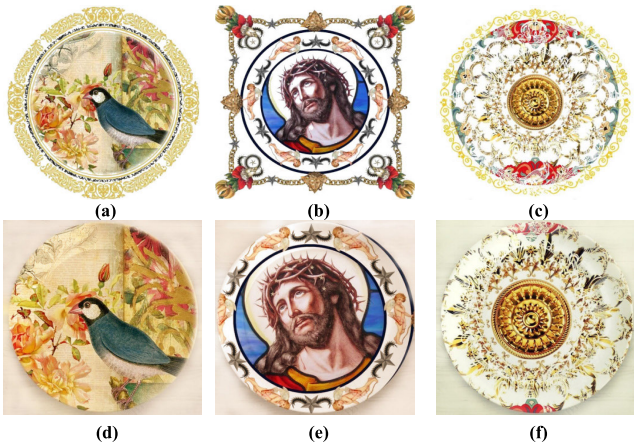


FIGURE 6. The generation of modern fashion style. (a) (b) (c) Ceramic disk patterns, (d) (e) (f) Physical ceramic disks.

When the weight of style is set to 0.6, and the weights of tone collocation and structure are set to 0.2, the relationship between pattern score and iteration times is shown in Fig.8. As can be seen from Fig.8, with the increase of the number of iterations, the maximum score presents a state of approximately monotonous increase. As the number of iterations increases, the increase of the highest score means that the unity of style is gradually improved.

D. ADAPTIVE FITNESS COMPARISON

It is further completed the fitness comparison of methods [11], [14], [20] and our method, and the experimental results are shown in Fig.9-10 and Tab.1-2. The following

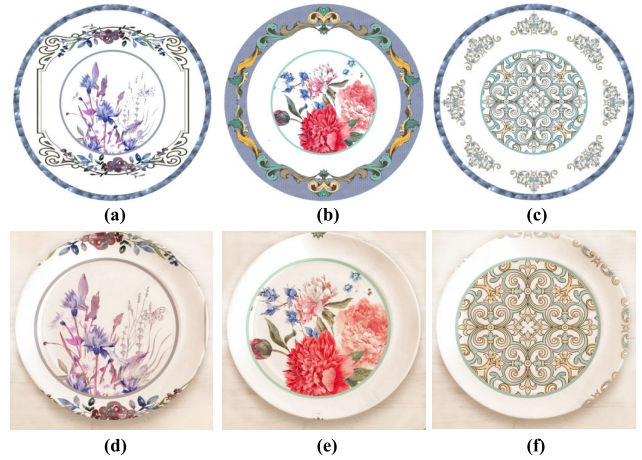


FIGURE 7. The generation of fresh style. (a) (b) (c) Ceramic disk patterns, (d) (e) (f) Physical ceramic disks.

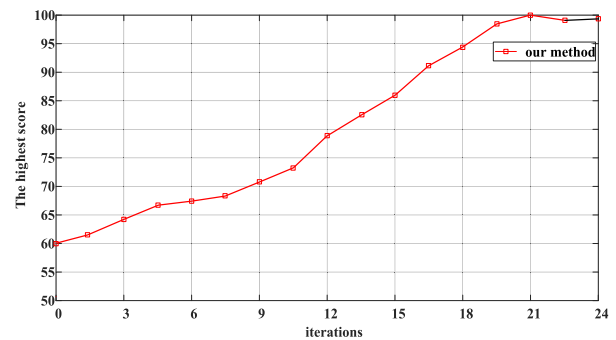


FIGURE 8. The relationship between pattern score and iteration times.

conclusions can be drawn from the figures and tables. (1) with the progress of the evolutionary process, the median point and width of the average fitness of the population of our method and methods [11], [14], [20] continuously decrease, and the population quality are continuously improved; (2) The user preference model of our method is combined with the individual fitness estimation. Compared with the fitness estimation method which only uses the predicted value, the operation efficiency of evolutionary selection is improved and the probability of finding a satisfactory solution is increased in our method; (3) By adopting our fitness estimation method, the quality of the optimal solution obtained is equivalent to the genetic algorithm based on the improved fitness function.

TABLE 1. Mean fitness comparison in midpoint change of our method and methods [11], [14], [20].

Midpoint of fitness methods	10	20	30	40	50
Method [11]	24.7	23.2	16.3	16.3	17.8
Method [14]	11.6	19.3	12.9	12.6	12.3
Method [20]	21.0	23.7	21.4	21.2	21.6
Our method	8.8	9.5	7.4	4.8	6.2

E. ALGORITHM PERFORMANCE COMPARISON

In order to compare the number of evolutionary algebras and satisfactory solutions, the proposed method and methods [11], [14], [20] were independently run for 50 times after

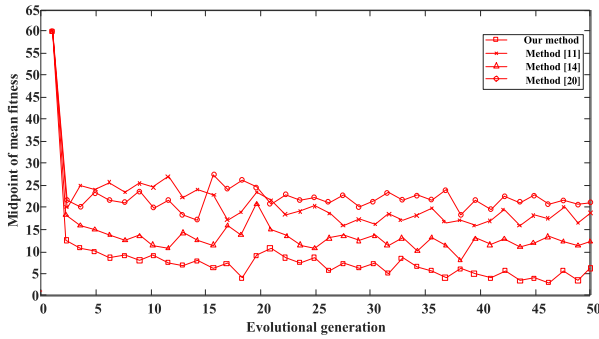


FIGURE 9. Mean fitness comparison in midpoint change curves of our method and methods [11], [14], [20].

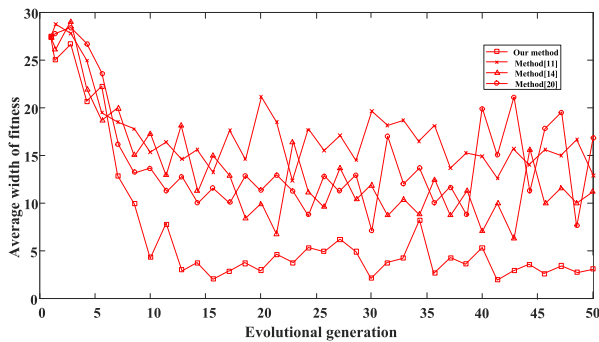


FIGURE 10. Average width of fitness comparison of our method and methods [11], [14], [20].

TABLE 2. Average width of fitness comparison of our method and methods [11], [14], [20].

Methods \ Average	10	20	30	40	50
Method [11]	15.5	21.7	19.5	15.0	12.6
Method [14]	17.4	10.0	12.0	7.0	10.3
Method [20]	13.6	11.7	7.3	19.5	17.1
Our method	4.1	2.9	2.5	5.5	3.1

setting parameters. Where, the satisfactory solution refers to the individual with the highest and second highest adaptive fitness of the exact number in each generation. The evolutionary generation (EG) statistics of the proposed method and methods [11], [14], [20] are shown in Fig.11 and Tab.3.

In Fig.11, our method has less evolutionary generation (EG). And the statistics of satisfactory solutions (SS) obtained by our method and methods [11], [14], [20] are shown in Fig.12 and Tab.3. It can be seen that our method obtains a large number of satisfactory solutions. This is because the similarity calculation of individuals in our method integrates the preference information of users, and in the process of fitness estimation of unevaluated individuals, the information of all individuals evaluated by users is integrated. Our method considers the weight of each component and the influence of component combination preference, so more information can be used. What's more, it also proves the effectiveness of calculating fitness on the basis of user preference.

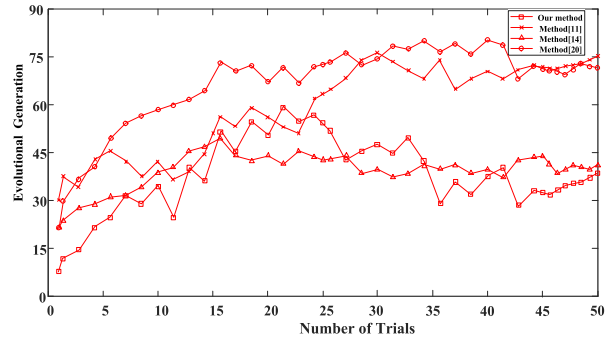


FIGURE 11. The evolutionary generation statistics of the proposed method and methods [11], [14], [20].

TABLE 3. Algorithm performance comparison.

Indexes \ Methods	10		20		30		40		50	
	EG	SS	EG	SS	EG	SS	EG	SS	EG	SS
Method [11]	41	41	56	50	76	61	70	56	71	60
Method [14]	38	81	44	82	39	79	40	79	41	82
Method [20]	53	48	67	53	74	57	80	61	75	55
Our method	34	97	51	109	47	106	37	99	39	99

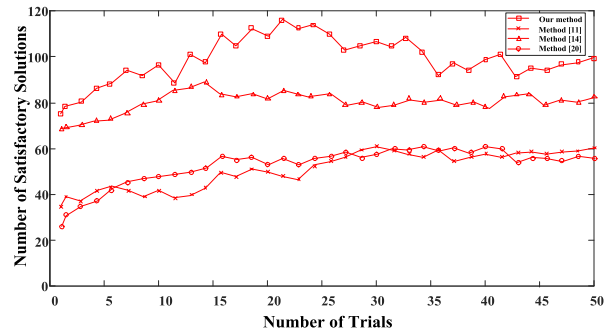


FIGURE 12. The statistics of satisfactory solutions of the proposed method and methods [11], [14], [20].

Combined with Fig.11 and Fig.12, it can be seen that our algorithm can obtain more satisfactory solutions in less evolutionary generations, which speeds up the convergence speed of our algorithm and shows better evolutionary optimization ability. With less evolutionary generation, the time consumption of our method is reduced, and the efficiency is improved.

V. CONCLUSION

When the core technology of ceramic firing tends to mature, the appearance design of ceramic disk products will become one of the key factors to gain competitiveness and occupy the market quickly. For a long time, scholars devote themselves to the research of product modeling and design, hoping to realize the automation and intelligence of product design process.

In this paper, interactive genetic algorithm based on user preference fitness is used to generate ceramic disk pattern. The improved method completed the calculation of user interest and style similarity, and realized the establishment of user preference model. The individual similarity calculation of the algorithm integrates the user preference information to make the calculation results more objective. Our algorithm

can generate different styles of ceramic disk patterns with satisfactory tonal collocation and structure. Besides, our method can obtain more satisfactory solutions in less evolutionary generations, which accelerates the convergence speed and shows better evolutionary optimization ability.

In the next stage, we plan to apply our method to the design of ceramic vases patterns.

REFERENCES

- [1] X. Xu, "Imagery non-photorealistic art processing in modern product design relying on an inline block optimization hierarchy tree algorithm," *EURASIP J. Image Video Process.*, vol. 2018, no. 1, pp. 1–11, Aug. 2018.
- [2] Y. Chen, X. Sun, D. Gong, Y. Zhang, J. Choi, and S. Klasky, "Personalized search inspired fast interactive estimation of distribution algorithm and its application," *IEEE Trans. Evol. Comput.*, vol. 21, no. 4, pp. 588–600, Aug. 2017.
- [3] D.-W. Gong, N.-N. Qin, and X.-Y. Sun, "Evolutionary algorithms for optimization problems with uncertainties and hybrid indices," *Inf. Sci.*, vol. 181, no. 19, pp. 4124–4138, Oct. 2011.
- [4] E. Sevinc and A. Cosar, "An evolutionary genetic algorithm for optimization of distributed database queries," *Comput. J.*, vol. 54, no. 5, pp. 717–725, May 2011.
- [5] Y. Li, G. Gong, and N. Li, "A parallel adaptive quantum genetic algorithm for the controllability of arbitrary networks," *PLoS ONE*, vol. 13, no. 3, Mar. 2018, Art. no. e0193827.
- [6] L. Bao, X. Y. Sun, Y. Chen, G. Y. Man, and H. Shao, "Restricted Boltzmann machine-assisted estimation of distribution algorithm for complex problems," *Complexity*, vol. 2018, Nov. 2018, Art. no. 2609014.
- [7] D. Gong, X. Ji, J. Sun, and X. Sun, "Interactive evolutionary algorithms with decision-maker's preferences for solving interval multi-objective optimization problems," *Neurocomputing*, vol. 137, pp. 241–251, Aug. 2014.
- [8] G. Raghuvanshi, N. Mishra, and S. Sharma, "Content based image retrieval using implicit and explicit feedback with interactive genetic algorithm," *Int. J. Comput. Appl.*, vol. 43, no. 16, pp. 8–14, Apr. 2012.
- [9] D. Gong, J. Sun, and X. Ji, "Evolutionary algorithms with preference polyhedron for interval multi-objective optimization problems," *Inf. Sci.*, vol. 233, pp. 141–146, Jun. 2013.
- [10] H. Kim and P. Kim, "Reliability–redundancy allocation problem considering optimal redundancy strategy using parallel genetic algorithm," *Rel. Eng. Syst. Saf.*, vol. 159, pp. 153–160, Mar. 2017.
- [11] R. Dou, Y. Zhang, and G. Nan, "Application of combined kano model and interactive genetic algorithm for product customization," *J. Intell. Manuf.*, vol. 30, no. 7, pp. 2587–2602, Oct. 2019.
- [12] S. Esfandyari and V. Rafe, "A tuned version of genetic algorithm for efficient test suite generation in interactive t-way testing strategy," *Inf. Softw. Technol.*, vol. 94, pp. 165–185, Feb. 2018.
- [13] Y.-P. Yang and X. Tian, "Combining users' cognition noise with interactive genetic algorithms and trapezoidal fuzzy numbers for product color design," *Comput. Intell. Neurosci.*, vol. 2019, pp. 1–11, Aug. 2019.
- [14] A. Wilson and B. M. Fazenda, "User-guided rendering of audio objects using an interactive genetic algorithm," *J. Audio Eng. Soc.*, vol. 67, nos. 7–88, pp. 522–530, Jul. 2019.
- [15] S. Koma, Y. Yamabe, and A. Tani, "Research on urban landscape design using the interactive genetic algorithm and 3D images," *Visualizat. Eng.*, vol. 5, no. 1, pp. 1–10, Feb. 2017.
- [16] X. Sun, D. Gong, Y. Jin, and S. Chen, "A new surrogate-assisted interactive genetic algorithm with weighted semisupervised learning," *IEEE Trans. Cybern.*, vol. 43, no. 2, pp. 685–698, Apr. 2013.
- [17] X. Sun, D. Gong, and W. Zhang, "Interactive genetic algorithms with large population and semi-supervised learning," *Appl. Soft Comput.*, vol. 12, no. 9, pp. 3004–3013, Sep. 2012.
- [18] A. Manfré, A. Augello, G. Pilato, F. Vella, and I. Infantino, "Exploiting interactive genetic algorithms for creative humanoid dancing," *Biologically Inspired Cognit. Archit.*, vol. 17, pp. 12–21, Jul. 2016.
- [19] R. Dou, C. Zong, and G. Nan, "Multi-stage interactive genetic algorithm for collaborative product customization," *Knowl.-Based Syst.*, vol. 92, pp. 43–54, Jan. 2016.
- [20] A. D. Piemonti, M. Babbar-Sebens, S. Mukhopadhyay, and A. Kleinberg, "Interactive genetic algorithm for user-centered design of distributed conservation practices in a watershed: An examination of user preferences in objective space and user behavior," *Water Resour. Res.*, vol. 53, no. 5, pp. 4303–4326, May 2017.
- [21] S. Janarthanam and S. Sukumaran, "Interactive genetic algorithm with relevance feedback for content based image retrieval," *Int. J. Current Res.*, vol. 8, no. 7, pp. 34948–34954, Jul. 2016.
- [22] Z. S. Darani and M. Kaedi, "Improving the interactive genetic algorithm for customer-centric product design by automatically scoring the unfavorable designs," *Hum.-Centric Comput. Inf. Sci.*, vol. 7, no. 1, pp. 1–18, Oct. 2017.
- [23] C. Li, D. Hu, Z. Song, F. Yang, Z. Luo, J. Fan, and P. X. Liu, "A vector grouping learning brain storm optimization algorithm for global optimization problems," *IEEE Access*, vol. 6, pp. 78193–78213, 2018.
- [24] C. Li, Z. Luo, Z. Song, F. Yang, J. Fan, and P. X. Liu, "An enhanced brain storm sine cosine algorithm for global optimization problems," *IEEE Access*, vol. 7, pp. 28211–28229, 2019.
- [25] Z. Song, J. Peng, C. Li, and P. X. Liu, "A simple brain storm optimization algorithm with a periodic quantum learning strategy," *IEEE Access*, vol. 6, pp. 19968–19983, 2018.
- [26] C. Li, Z. Song, J. Fan, Q. Cheng, and P. X. Liu, "A brain storm optimization with multi-information interactions for global optimization problems," *IEEE Access*, vol. 6, pp. 19304–19323, 2018.
- [27] C. Li, Z. Niu, Z. Song, B. Li, J. Fan, and P. X. Liu, "A double evolutionary learning moth-flame optimization for real-parameter global optimization problems," *IEEE Access*, vol. 6, pp. 76700–76727, 2018.
- [28] N. Alaoui, A. B. H. Adamou-Mitiche, and L. Mitiche, "Effective hybrid genetic algorithm for removing salt and pepper noise," *IET Image Process.*, vol. 14, no. 2, pp. 289–296, Feb. 2020.
- [29] L. X. We and Y. Zhang, "Research on the key technologies of ceramic pattern design system," in *Proc. 5th Int. Conf. Intell. Syst. Design Eng. Appl. (ISDEA)*, Hunan, China, Jun. 2014, pp. 871–875.
- [30] M. Khajeh, P. Payvandy, and S. J. Derakhshan, "Fashion set design with an emphasis on fabric composition using the interactive genetic algorithm," *Fashion Textiles*, vol. 3, no. 1, pp. 1–16, Apr. 2016.
- [31] H. Fu, B. Wu, Y. Shao, and H. Zhang, "Perception oriented haze image definition restoration by basing on physical optics model," *IEEE Photon. J.*, vol. 10, no. 3, pp. 1–16, Jun. 2018.
- [32] C. Yiakoumettis, N. Doulamis, G. Miaoulis, and D. Ghazanfarpour, "Active learning of user's preferences estimation towards a personalized 3D navigation of geo-referenced scenes," *Geoinformatica*, vol. 18, no. 1, pp. 27–62, Jan. 2014.
- [33] L. Wang, X. Ma, and J. Zhang, "Feature screening for ultrahigh-dimensional additive logistic models," *J. Stat. Planning Inference*, vol. 205, pp. 306–317, Mar. 2020.
- [34] Y. Zeng and K. Zhao, "Optimal decay rates for a chemotaxis model with logistic growth, logarithmic sensitivity and density-dependent production/consumption rate," *J. Differ. Equ.*, vol. 268, no. 4, pp. 1379–1411, Feb. 2020.
- [35] E. Fonseca, P. T. Fiadeiro, M. V. Bernardo, A. Pinheiro, and M. Pereira, "Assessment of speckle denoising filters for digital holography using subjective and objective evaluation models," *Appl. Opt.*, vol. 58, no. 34, pp. G282–G292, Dec. 2019.
- [36] T. Seyama and M. Munetomo, "Development of a multi-player interactive genetic algorithm-based 3D modeling system for glasses," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Vancouver, BC, Canada, Jul. 2016, pp. 846–852.
- [37] G. Li, S. Jiang, C. Chen, P. Brunner, Z. Wu, G. Schalk, L. Chen, and D. Zhang, "IEEGview: An open-source multifunction GUI-based MATLAB toolbox for localization and visualization of human intracranial electrodes," *J. Neural Eng.*, vol. 17, no. 1, Dec. 2019, Art. no. 016016.



HUAFEI CAI received the M.S. and Ph.D. degrees from the Jingdezhen Ceramic Institute, Jiangxi, China. She was a Visiting Scholar with Coventry University, U.K., in 2017. She is currently an Associate Professor with the Guangdong University of Finance and Economics and a Tutor for master's students. She has presided over and participated in 11 national, provincial, and ministerial projects, including one National Social Science Fund. She has published more than

15 articles. Her ceramic art works have been exhibited and evaluated more than 20 times at the provincial or ministerial level, among which, she has received nine gold, silver, and bronze prizes.

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