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RESEARCH ARTICLE

Optimization Design of Product Form Driven by Image Cognitive Friction

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ABSTRACT To balance the image cognitive friction of users and designers regarding product form, based on noncooperative game theory, a product form optimization design method was proposed to generate product forms that meet the common expectations of users and designers. First, the semantic difference method was used to construct the image cognitive spaces of users and designers. Second, based on the theory of computational aesthetics, production rules were used to structurally describe the aesthetic knowledge of product form; the aesthetic index values of product form were calculated; and two gray-box image evaluation models of design features, aesthetic indexes, and images were established with the method of quadratic polynomial stepwise regression. Finally, using the image cognitions of users and designers as game participants and the two image evaluation models as profit functions, a noncooperative game model was established, and a quantum genetic algorithm was used to obtain the Nash equilibrium solution of the model to achieve the optimal design of the product form. Taking the optimal design of a sphygmomanometer as an example, the rationality and effectiveness of the method are verified.

INDEX TERMS Cognitive friction, product form, optimization design, image evaluation, noncooperative game theory.

I. INTRODUCTION

With the improvement of material living standards, people's consumption concepts are gradually changing, and there is a significant positive correlation between consumption behavior and the aesthetic quality of products. In 2003, Gernot named this new economic form the aesthetic economy. In the era of the aesthetic economy, users are increasingly valuing the spiritual functions of products and paying more attention to the aesthetic and emotional experiences brought by enjoyable technology. In mature technological fields, the functional technology of products is only a basic condition for entering the market. The gaps in functionality and technology between products from different manufacturers are decreasing, and there is a widespread phenomenon of homogenization. Currently, the aesthetic quality of the product form is one of the key factors in consumer behavior decision-making.

The intelligent design of product form applies modern information technology, using computer simulation of human visual aesthetic evaluation and aesthetic creativity, to carry out intelligent design, simulation, and visualization of product form schemes. The intelligent design of product form can generate many novel and inspirational form design schemes and is gradually becoming a popular topic in design research [1].

The fitness function of a product intelligent design system is usually constructed from the perspective of product form image evaluation and aesthetic evaluation. For example, Zhou et al. used crawling tools to construct a dataset for the aesthetic evaluation of frontal car images, designed a deep convolutional neural network (CNN) for aesthetic evaluation, and used generative adversarial networks (GANs) to generate shape sketch schemes for the front face of the car [2]. Li et al.

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identified design variables and emotional responses through design analysis, established a predictive model for emotional responses related to design variables using support vector regression (SVR), and constructed a multiobjective optimization model involving maximum emotional response [3].

The commonly used artificial intelligence algorithms of product intelligent design systems include the genetic algorithm, swarm intelligence algorithm, interactive evolutionary algorithm, and hybrid algorithm. For example, Zhang et al. constructed a product Kansei image evaluation system using artificial neural networks (ANNs) and established a beverage bottle Kansei image form evolution system using genetic algorithms [4]. Yang used a consensus model to measure the consistency of consumer opinions, combining an advanced particle swarm optimization algorithm (PSO) with a linearly decreasing inertia weight (LDW) method to achieve consistency by minimizing adjustments to consumer opinions, and constructed an electronic scooter design system [5].

At present, research on the intelligent design of product form has achieved some advancements, but it mainly considers the perspective of user imagery and aesthetic cognition. There is relatively little research on the imagery and aesthetic cognition of designers, who have undergone long-term professional training and possess professional aesthetic abilities, taste, perspective, and good foresight in imagery and aesthetic cognition. Therefore, it is necessary to study the imagery and aesthetic cognition of designers [6]. Due to differences in learning experiences, professional knowledge, and thinking styles between users and designers, there is inevitably cognitive friction [7]. The imagery and aesthetic cognition of users and designers can be integrated for comprehensive evaluation, reducing communication barriers between users and designers. This can not only prevent misunderstanding of elegant design works but also avoid the vulgarization of design works. Therefore, balancing cognitive friction is an important way to solve cognitive conflicts between designers and users and is a key link in obtaining user recognition for product form solutions.

To address the above problems, starting from the cognitive differences between users and designers, the Kansei engineering and computational aesthetics methods are introduced to construct the image evaluation models of users and designers, respectively. Taking the image cognitions of users and designers as the game players and the two image evaluation models as the profit functions, a product form optimization design method based on noncooperative game theory is proposed. By evaluating the images of research cases, this design system can intuitively reflect the magnitude of cognitive friction. Through a cognitive friction game model, cognitive friction is continuously corrected, filtering out product forms that meet the cognitive needs of users and designers. This method can reduce cognitive conflicts between designers and users, improve design efficiency, and meet the aesthetic needs of users.

The rest of the paper is organized as: In Section II, we provide a complete review and analysis of the image cognitive friction. Section III presents the basic framework of the optimization design of product form. In Section IV, we describe the preliminary results of an empirical study to verify the noncooperative game model of cognitive friction. Section V discusses implication of the experimental results, and performs a comparative analysis with other product form design method. Finally, we conclude the paper and discuss the future research directions in Section VI.

II. LITERATURE REVIEW

A. IMAGE EVALUATION OF PRODUCT FORMS

Image evaluation is a mapping model between product form design features and images using various mathematical methods. The research on design features mainly focuses on the key curve nodes, modeling units, or functional units of the product. Image mining often uses psychological introspective analysis methods, and images are obtained through questionnaire surveys. The commonly used techniques for constructing product image evaluation models include neural networks, support vector machines, gene regulatory networks, fuzzy theory, rough set theory and gray theory. The image evaluation model can not only reveal the influence of various form elements on image formation but also serve as the fitness function of intelligent design systems. It is an important link in product form intelligent design.

In recent years, image evaluation research has achieved good results in application modes, experimental methods and modeling technology. For example, Shen et al. quantified the qualitative characteristics of product images and design elements by using fuzzy definitions and discussed the relationship between images and design elements by using multiple linear regression and a back propagation (BP) neural network [8]. Xue et al. used the semantic difference method to obtain image values, identified design elements that have an impact on product image using quantitative theory Type I, and established a product image design decision model [9]. Wang et al. used the semantic difference method to measure users' image needs, obtained key image words through factor analysis, and used partial correlation analysis to determine the connection between design elements and images [10]. Yang et al. introduced electroencephalogram (EEG) and eye tracking (ET) technologies to establish a space for user image needs and used partial least-squares regression to establish a correlation model between shape design elements, EEG and ET indicators, and image values [11].

The traditional product form image evaluation model is usually constructed using a black box method that takes design features as input and images as output. Although the black box modeling method does not require an understanding of the internal mechanisms of the image recognition system, the internal structure of the resulting model is also unknown [12]. Moving from the visual perception of design features to the formation of images involves complex information processing, including much tacit knowledge, such as aesthetic and emotional cognition. Here, by introducing the aesthetic index, a gray box model, design features - aesthetic indexes - images, is constructed to evaluate the product form image. The general expression of the model is as follows:

$$AM = f\left(g\left(M\right)\right) \tag{1}$$

where M is the set of design features, AM is the image, g represents the functional relationship between aesthetic indexes and design features, and f represents the functional relationship between images and aesthetic indexes. This model can simulate the information processing of cognitive activities to a certain extent. The construction of this gray box model requires prior knowledge related to visual cognitive mechanisms and posterior knowledge for system recognition using data [13]. Prior knowledge is based on computational aesthetics, and production rules are used to express aesthetic knowledge, while posterior knowledge is used to express the internal relations of unknown systems by quadratic polynomial stepwise regression [14].

B. COGNITIVE FRICTION

Research on design cognition models focuses on the external expression, reasoning process and concept emergence of creative intelligence based on nonstructural data such as text, language and sketches [15]. Human visual cognition is actually a type of information processing. Designers stimulate people's sensory organs by applying a series of symbolic language elements to the product form, and the impression of the product arises after the information is processed by the brain. The generation of design schemes involves not only the shaping of the product form by designers but also the interaction between the encoding of product form information by designers and the process of decoding user cognitive information [16]. In addition to the genetic and congenital factors of people's personalities, there are considerable differences in people's experiences and memories due to the different external environments during their growth. Therefore, the differentiation of people's cognition of products is inevitable.

In view of the differences and asymmetry of cognitive information, Cooper et al. proposed the concept of cognitive friction. In the field of product design, cognitive friction can be seen as a gap between users and designers in terms of aesthetic cognition [17]. Designers' products cannot fully meet users' expectations, and this phenomenon may cause users to feel confused when using products. In recent years, many scholars have studied cognitive differences from different perspectives. For example, Hsu et al. used the semantic differential (SD) method to investigate the cognitive differences between designers and users regarding phone forms and explored the relationship between the image evaluation of phone form and design elements [18]. Fu et al. identified user interface perception spaces through sorting and calculated the interface perception similarity between users and designers. They found significant differences in user interface preferences and the attributes that affect these preferences [19]. Zhang et al. introduced relative entropy to balance cognitive differences among users, designers, and engineers and then built a comprehensive evaluation model [20]. The above research focused on investigating the differences in image cognition between users and designers, as well as the impact of design elements on image cognition differences. However, further research is needed on product form optimization design driven by image cognitive friction.

C. GAME THEORY

Game theory is used to study decision-making when the behaviors of each subject directly interact, as well as the equilibrium problem of this kind of decision-making. It is an important method for multiattribute decision-making [21]. There is no binding agreement between the participants in the game process. The strategy is chosen in the present strategy space to acquire the optimal strategy under restrictions and interactions, and this is referred to as a noncooperative game. As game theory has solved many multiagent problems in economics, many scholars have begun to study the application of game theory to different fields. For example, Tang et al. introduced a method for detecting and managing noncooperative behavior through a hierarchical consensus model, using the minimum spanning tree clustering algorithm to classify experts [22]. Yang and Ding combined the advantages of variable expert weights and q-rung orthopair fuzzy sets to design a two-person noncooperative fuzzy matrix game method to handle competitive strategy group decision-making problems [23]. Li et al. designed a noncooperative game forwarding strategy based on the prior mutual ignorance of decision-making between mobile network nodes to meet the actual needs of actual mobile networks [24].

In addition, other scholars have studied typical game models such as the Stackelberg game and the cooperative game, which are applied to different practical problems. For example, Fiez established some connections between the concepts of Nash and Stackelberg equilibria and characterized the condition that the attractive critical point of simultaneous gradient descent in zero-sum games is a Stackelberg equilibrium. In addition, we proved that the only stable critical point of Stackelberg gradient dynamics is the Stackelberg equilibrium in zero-sum games [25]. Teng et al. used cooperative game theory as a method of analyzing the profit distribution among the designer, construction contractor, owner and building information modeling (BIM) consultant [26]. Yang et al. constructed a two-level optimization model that considers Stackelberg and cooperative games, with flexible participation in higher-level games within a park system as variable factors. The proposed two-stage solution algorithm was used for multiscenario optimization solution analysis [27].

The differences in the image and aesthetic cognition between users and designers can easily lead to obstacles and conflicts in the encoding and decoding of product form information. Here, the game theory method is used to predict

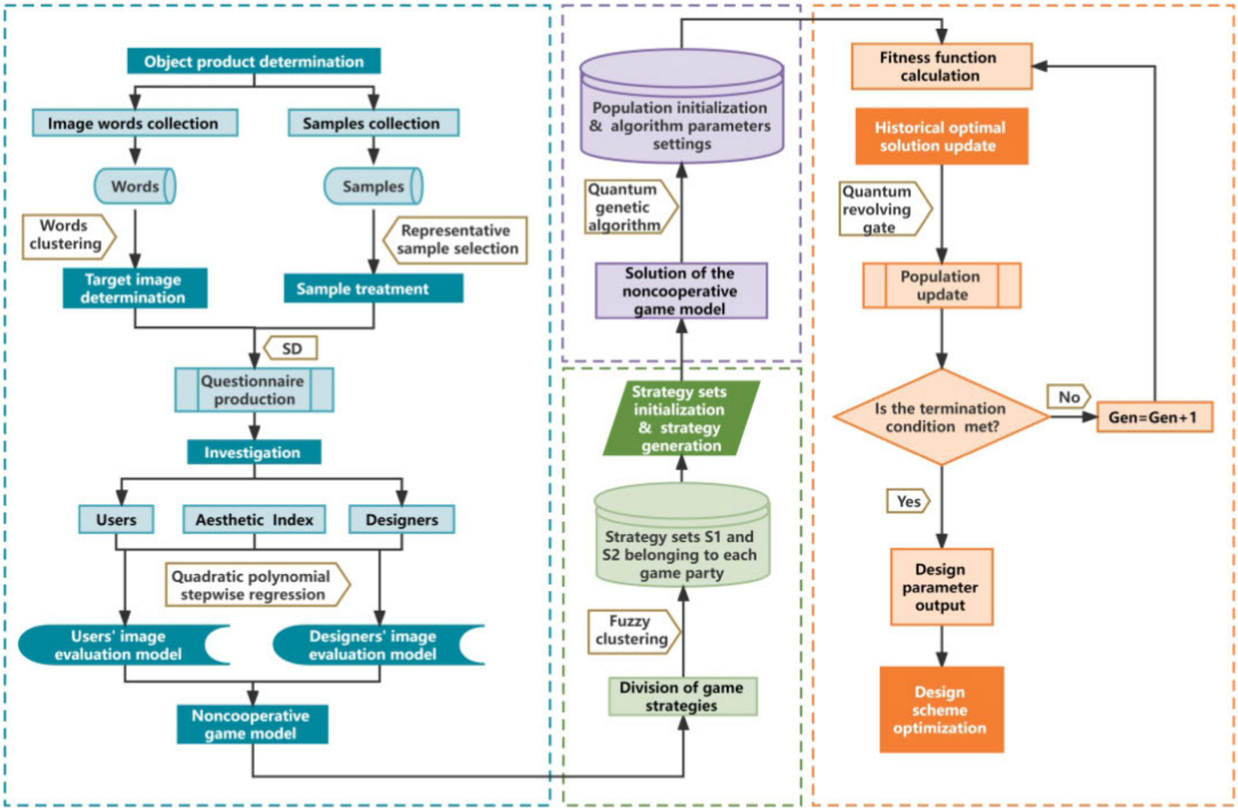


FIGURE 1. Research framework.

the image and aesthetic cognition of users and designers, explore the optimization design strategy for the product form, balance the cognitive friction between users and designers, and improve the smoothness of the encoding and decoding interactions. Both users and designers can not only fully grasp the potential market demand trends but also consider the innovative, forward-looking and leading nature of product aesthetics.

III. METHOD

The research framework of the optimization design of a product form driven by image cognitive friction is shown in Fig. 1, and the steps are as follows:

Step 1: The research object and target image are identified, samples are screened using the Jiro Kawakita (KJ) method, and image words are screened using the KJ method and cluster analysis.

Step 2: The cognitive space of images between users and designers is established, and the SD method is used to evaluate their cognitions of images. The cognitive differences between them are analyzed.

Step 3: By introducing computational aesthetics methods based on an aesthetic index system and formulas, the aesthetic index values of the samples are calculated.

Step 4: Using quadratic polynomial stepwise regression, a model for user and designer image evaluation is established, and the two models are used as profit functions in subsequent game models.

Step 5: Using the image cognitions of users and designers as the game parties, a noncooperative game model is established, and a quantum genetic algorithm is used to solve the model, achieving the optimal design of the product form.

A. AESTHETIC INDEX

The product form is disordered information with multiple features and complex content. This disordered information is processed by a visual information processor and transformed into structured and ordered information that conforms to the cognitive coding of the brain. The construction of orderly information is the basis of a series of aesthetic cognitive operations, such as visual information storage, retrieval, extraction, reorganization, synthesis, reasoning, and decision-making. Aesthetic principles and gestalt principles are two recognized aesthetic paradigms in aesthetic research. They are connected with the production rules of visual information processing and are a kind of structured and orderly information. Product form information is structured and expressed using computational aesthetics methods, and various aesthetic calculation formulas for product form are established. These formulas reveal the quantitative relationship between product form characteristics and aesthetic indexes, clearly express implicit aesthetic cognitive knowledge, and transform disordered product form information into orderly information. Based on the morphological layout feature of the research object, nine aesthetic indexes that are more key in product morphological design are selected, namely, balance, equilibrium, symmetry, proportion, density, sequence, proportional similarity, unity, and simplicity. The specific interpretation and calculation formula of each aesthetic index can be found in [28].

B. QUADRATIC POLYNOMIAL STEPWISE REGRESSION

Due to the complexity of image recognition, there is a potential connection between various product forms and aesthetic indexes, so image evaluation is a complex multivariable, nonlinear coupling problem [29]. The commonly used theories of multiple linear regression and quantification-I theory can be used to construct accurate mathematical correlation models, but they have the disadvantages of relying too much on linear assumptions and being unable to deal with nonlinear relationships. In this paper, utilizing the quadratic polynomial stepwise regression method, a multiple regression model for the aesthetic index and image evaluation is established [30]. Stepwise regression analysis can automatically select independent variables that are important for the establishment of regression equations. This method tests the significance of their effect on dependent variables while introducing independent variables until all significant independent variables are introduced [31]. If the current independent variable becomes insignificant due to the independent variables introduced later, it should be eliminated to ensure that the current regression equation contains only the independent variables that play a significant role in determining the dependent variable. The general expression of the quadratic polynomial regression equation is as follows:

$$Y = \beta_0 + \sum_{i=1}^{m} \beta_i X_i + \sum_{i=1}^{m} \beta_{ii} X_i^2 + \sum_{i<1}^{m} \beta_i X_i X_j \tag{2}$$

where Y is the fitted value of the image evaluation; X_i and X_j are the i-th and j-th aesthetic indexes; m is the number of aesthetic indexes; and β_0, β_i, β_{ii}, and β_{ij} are the coefficients of the constant term, the first order, the quadratic term and the cross term, respectively.

C. GAME THEORY

1) NONCOOPERATIVE GAME MODEL

There is no coordination between the image cognitions of users and designers, and the fusion of the cognitive friction between the two is a noncooperative game problem. The noncooperative game includes three elements: the decision-maker N_i, strategy set S_i and profit function U_i. In a round of games, each participant selects his or her strategy S_i, and then, the strategy set composed of the strategies of all participants can be expressed as $S = \{S_1, S_2, \cdots, S_m\}$. The profit U_i of each player is a function of the strategy. The noncooperative game decision model can be expressed as $G = \{N_i; S_i; U_i\ (i = 1,2, \cdots m)\}$. The image cognitions of users and designers can be regarded as game parties N_1 and N_2 in the game decision, the image evaluation functions of both are regarded as profit functions U_1 and U_2, the design variables of product form are regarded as the strategy spaces of all game parties, and the value range of each design variable is regarded as the constraint condition of the game problem.

2) DIVISION OF GAME STRATEGIES

Since the design variables of product form are shared by the two profit functions, the design variables need to be divided into strategy sets that belong to each game party using fuzzy cluster analysis. The calculation steps are as follows:

Step 1: The partial derivative of design variable X_j relative to the game player's image evaluation functions is as follows:

$$\delta_j = \left\{ \frac{\partial X_j}{\partial N_1}, \frac{\partial X_j}{\partial N_2} \right\} = \{\delta N_1, \delta N_2\} \tag{3}$$

where δ_j is the j-th set of design variable factors.

Step 2: Let the clustering object be $\delta_j = \{\delta_{j1}, \delta_{j2}, \cdots, \delta_{ji}, \cdots, \delta_{jm}\}$ $(j = 1, 2, \cdots, n)$, where δ_j represents the j-th set of design variable factors influencing all m objective functions. The total number of clustering objects is $\delta = \{\delta_1, \delta_2, \cdots, \delta_j, \cdots, \delta_n\}$. Then, fuzzy clustering is performed.

Step 3: The fuzzy similarity matrix $R = (r_{kl})_{n\times n}$, with $0 \le r_{kl} \le 1$ and $(k, l = 1, 2, \cdots, n)$, is established, where r_{kl} represents the degree of association similarity of the classification objects (design variables x_k and x_l, that is, clustering objects δ_k and δ_l). There are many methods of calculating r_{kl}, and absolute subtraction is commonly used.

$$R = \begin{bmatrix} r_{11}, r_{12}, \cdots r_{1l}, \cdots r_{1n} \\ r_{21}, r_{22}, \cdots r_{2l}, \cdots r_{2n} \\ \vdots \vdots \cdots \vdots \cdots \vdots \\ r_{k1}, r_{k2}, \cdots r_{kl}, \cdots r_{kn} \\ \vdots \vdots \cdots \vdots \cdots \vdots \\ r_{n1}, r_{n2}, \cdots r_{nl}, \cdots r_{nn} \end{bmatrix} \tag{4}$$

$$r_{kl} = \begin{cases} 1 & k = l \\ 1 - M \sum_{i=1}^{m} |\delta_{ki} - \delta_{li}| & k \ne l \end{cases} \tag{5}$$

where M is the appropriate coefficient chosen to make $0 \le r_{kl} \le 1$.

Step 4: The transitive closure matrix $t(R)$ of the fuzzy similarity matrix R can be obtained by using the square automorphism method, and the fuzzy equivalent matrix $\widehat{R} = t\,(R)$ can be acquired. That is, starting from R, the square method is utilized to calculate $R \to R^2 \to R^{2^2} \to R^{2^3} \to \cdots \to R^{2^k} \cdots$ in turn. When $R^{2^{k+1}} = R^{2^k}$ is satisfied for the first time, $\widehat{R} = R^{2^k}$, R^{2^k} is the transitive closure matrix $t(R)$ of R, where $R^2 = R \circ R$ represents a Boolean operation.

Step 5: Taking the proper confidence level value as $\lambda \in [0, 1]$, the matrix is cut based on the level λ of the fuzzy equivalent matrix $\widehat{R}$, and the equivalent relation matrix R_λ is acquired. Finally, the different optimization design variables are classified as the strategy sets belonging to each game party.

3) SOLUTION OF THE NONCOOPERATIVE GAME MODEL

The algorithmic steps for determining the Nash equilibrium strategy of the noncooperative game decision model are as follows:

Step 1: The objective function is determined, and the parameters are set, including the variables of morphological design, constraint conditions, and iteration accuracy ε.

Step 2: The influencing factors of the design variables regarding the game players' profits are calculated, and the strategy sets S_1 and S_2 belonging to each player are acquired utilizing fuzzy clustering.

Step 3: The initial game is analyzed, and the strategy sets $S^o = \left\{S_1^o, S_2^o\right\}$ are generated randomly in the strategy set space $S = \{S_1, S_2\}$.

Step 4: The initial strategy sets selected by all players except S_i^o in the initial strategy set S^o are marked as S_{-i}^o, $i = 1, 2$. Taking the profit functions $U_1(S), U_2(S)$ of the two game players as the optimization goals and keeping S_{-i}^o unchanged, the strategy sets S_1 and S_2 belonging to each player undergo corresponding single-objective optimization with a quantum genetic algorithm; that is, for the i-th game player, in its strategy set S_i, the optimal strategy set S_i^* to maximize the game's profit $U_i\left(S_i^*, S_{-i}^o\right) \rightarrow \max$ and meet the constraints of $h_k\left(S_i^*, S_{-i}^o\right) \leq 0, k = 1, 2, \cdots, q$, is found. (That is, if $U_i\left(S_i^*, S_{-i}^o\right) \geq U_i\left(S_i, S_{-i}^o\right)$, $S^* = \left(S_1^*, S_2^*\right)$ is called a Nash equilibrium.)

Step 5: Supposing $S^{(1)} = S_1^* \cup S_2^*$, the distance between the strategy sets S^o and $S^{(1)}$ is calculated. If it meets the convergence criterion $\left\|S^{(1)} - S^{\mathrm{o}}\right\| \leq \varepsilon$, where ε is an arbitrarily small positive number, the game ends; otherwise, S^o is replaced by $S^{(1)}$, the procedure goes back to step 2, and the iterative calculation is repeated until the end condition is met. The algorithm flow is shown in Fig. 1.

In Step 4, a quantum genetic algorithm is utilized for optimization. This method is an intelligent optimization algorithm combining quantum computing and a genetic algorithm [32]. Due to the disadvantages of the slow convergence speed and poor solution accuracy of the genetic algorithm, the coding algorithm combined with quantum computing can effectively improve the efficiency and quality of the model solution. The process of the quantum genetic algorithm is as follows:

Step 1: The population is initialized, and the algorithm parameters are set, including the maximum population number "Maxgen", the historical optimal fitness value (image value) "$\mathrm{Y_{best}}$" and its corresponding morphological individual parameter "$\mathrm{Y_{besti}}$". In this experiment, the fitness function is the image evaluation function of users and designers.

Step 2: The population is measured, and the probability amplitude matrix is converted to a binary matrix.

Step 3: The fitness function value is calculated. The optimal fitness value "T" in the current population and the corresponding morphological individual "T_i" are retained.

Step 4: If the current optimal solution is better than the historical optimal solution, the historical optimal solution is updated to $\mathrm{Y_{best}} = \mathrm{T}$ and $\mathrm{Y_{besti}} = \mathrm{T}_i$; otherwise, the procedure moves to the next step.

Step 5: The population is updated by a quantum revolving gate.

Step 6: The number of iterations is increased by 1, and steps 2-6 are repeated. When the termination condition is met, the cycle ends.

Step 7: The optimal fitness value "$\mathrm{Y_{best}}$" and the corresponding optimal shape individual "$\mathrm{Y_{besti}}$" are output.

IV. EMPIRICAL STUDY

A. DETERMINATION OF THE RESEARCH OBJECT AND TARGET IMAGE

A home sphygmomanometer is taken as an example to verify the effectiveness of the proposed method. In the early stage, 84 sphygmomanometer pictures and 93 image words describing the form of the sphygmomanometer were collected through journals, websites and other channels. According to the principles of covering all basic design elements and ensuring sample typicality, 10 experts were invited to use the KJ method to screen the 84 samples to obtain 24 representative samples, and wireframes were drawn in Rhino software, as shown in Table 1. A total of 93 image words were compared and analyzed regarding their meanings, homogenous image words were deleted, and 32 image words were ultimately selected. The importance of the above 32 words was investigated, and the subjects were asked to select 9 image words that were most relevant to the purchase of the sphygmomanometer. Fifty subjects participated in the survey. According to the survey results, the image words with the top 9 importance values were as follows: "concise", "harmonious", "cozy", "lively", "exquisite", "personalized", "elegant", "fashionable" and "advanced".

B. ESTABLISHING THE IMAGE COGNITIVE SPACE

Based on 24 representative samples and 9 image words, a 5-level SD questionnaire was created. The semantic scale is explained as follows. The image word "advanced" is taken as an example. A score of 1 means not at all advanced, 2 means not very advanced, 3 means neutral, 4 means somewhat advanced, and 5 means very advanced. Thirty-three users and 33 designers were investigated, and the detailed demographic and background information of the participants is shown in Table 2. The dimension of the 9 image words was reduced to 3 through cluster analysis, and the image words closest to the cluster center were selected as the representatives of each type of image word to form the image cognitive spaces of users and designers; the words chosen were "concise", "cozy" and "advanced". The image evaluation results for

TABLE 1. Sample of sphygmomanometer forms.

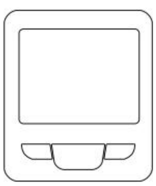
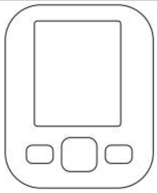
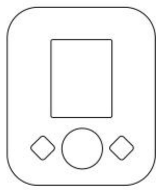
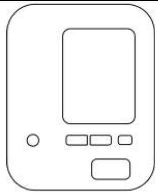
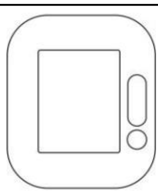
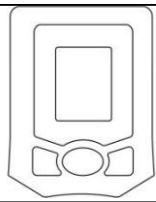
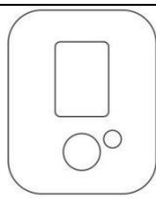
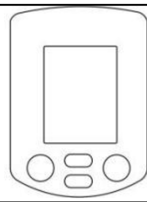
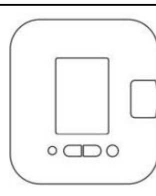
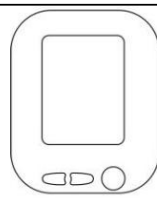
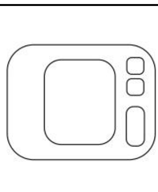
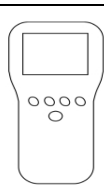
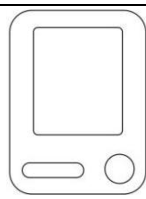
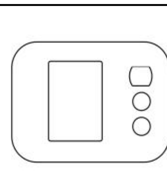
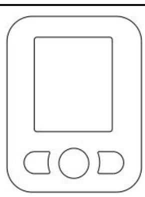
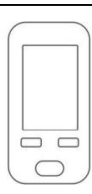
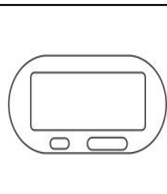
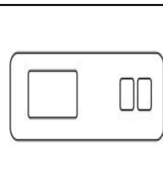
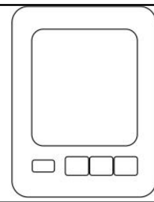
Sample						
Number	(1)	(2)	(3)	(4)	(5)	(6)
Sample						
Number	(7)	(8)	(9)	(10)	(11)	(12)
Sample						
Number	(13)	(14)	(15)	(16)	(17)	(18)
Sample						
Number	(19)	(20)	(21)	(22)	(23)	(24)

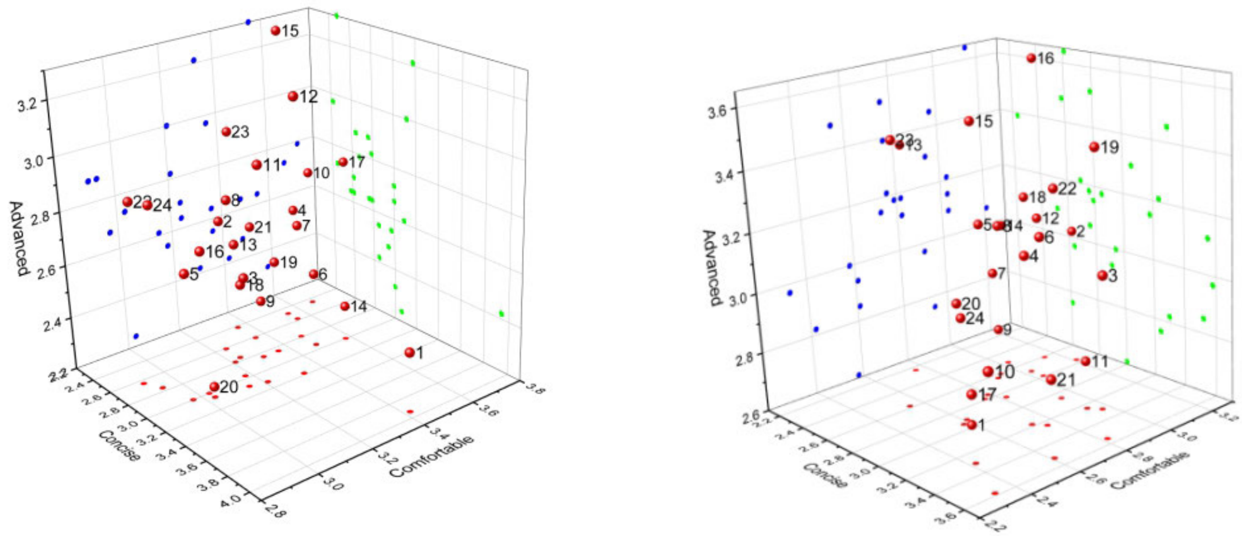
TABLE 2. Demographic and background information of the participants.

Characteristic	Users	Designers	Characteristic	Users	Designers
Sex			Household income		
Male	17	15	Less than $10000	6	0
Female	16	18	$10000-$30000	19	20
Age			Greater than $30000	5	8
Less than 40	1	23	No response	3	5
40-60	7	10	Type of residence		
Greater than 60	25	0	Home	24	12
Education			Apartment	9	21
High school or less	18	0	Residential location		
College degree or some college	13	33	Urban	26	33
No response	2	0	Rural	7	0
Marital status					
Unmarried	1	21			
Married	32	12			

the users and designers on each sample are shown in Table 3. Origin software was used to draw the image cognitive spaces of users and designers for the 24 research samples, as shown in Fig. 2.

TABLE 3. Image evaluation values of users and designers.

Sample	Users			Designers			Absolute difference		
	Concise	Cozy	Advanced	Concise	Cozy	Advanced	Concise	Cozy	Advanced
1	3.94	3.42	2.42	3.00	2.58	2.61	0.94	0.84	0.19
2	2.61	3.24	2.70	2.76	3.21	3.06	0.15	0.03	0.36
3	3.09	3.15	2.61	3.55	2.82	3.12	0.46	0.33	0.51
4	2.58	3.55	2.64	3.18	2.73	3.15	0.60	0.82	0.51
5	3.00	2.97	2.67	2.76	2.79	3.18	0.24	0.18	0.51
6	2.94	3.48	2.48	3.24	2.76	3.21	0.30	0.72	0.73
7	2.79	3.48	2.64	2.64	2.91	2.97	0.15	0.57	0.33
8	2.79	3.21	2.82	2.85	2.82	3.18	0.06	0.39	0.36
					…				
24	2.76	2.94	2.88	2.91	2.61	2.94	0.15	0.33	0.06



(a) Image cognitive space of users

(b) Image cognitive space of designers

FIGURE 2. Image cognitive space.

Table 3 and Figure 2 show that there is a significant difference between the image cognitions of users and designers. Taking sample 6 and the image word "advanced" as an example, the user score is 2.48, while the designer score is 3.21. The difference in the image evaluation values of the participants is 0.73. Through a followup survey of users and designers, the main reasons for the user evaluation were as follows: the screen size is small, the design is very symmetrical, and it is uninteresting, so the overall feeling is that the design is not very advanced. The main evaluation reasons of designers are as follows: the overall form is shield-shaped, the novelty is good, the keys fit well with the form, and the overall feeling gives a certain sense of advancement. There are great differences in the starting points, standards and weights of the two scores. Therefore, it is meaningful to introduce the cognitive difference between the two as a driving force into research on product form design.

C. CALCULATION OF AESTHETIC INDEXES

According to the requirements of the computational aesthetics method, a coordinate system was drawn to calculate the aesthetic index of the front shape of the sphygmomanometer, as shown in Fig. 3. The coordinate origin is located at the center of the shape contour of the sphygmomanometer. Since the sample size does not affect the index calculation results, the sample width is standardized to a unified value here.

Based on the principle of visual cognitive simplification, the first-level morphological characteristics of 24 sphygmomanometer samples were extracted for aesthetic index calculation, namely, the external contour, screen and various

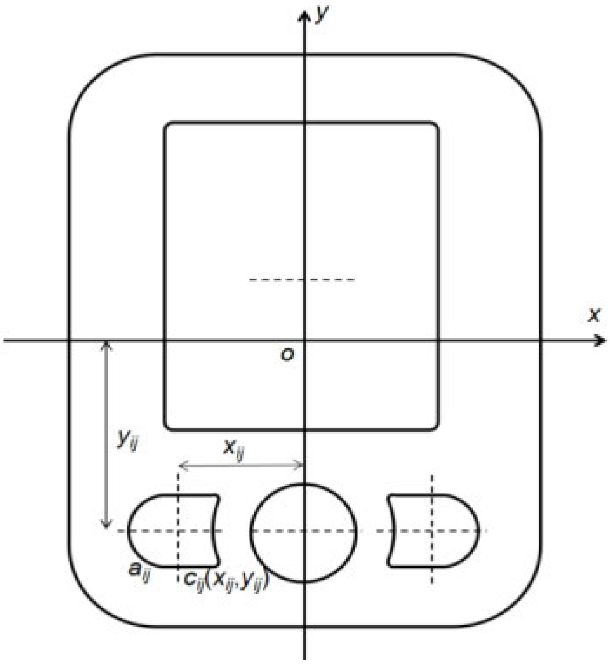


FIGURE 3. Coordinate chart of the aesthetic index for calculation.

buttons. Rhino software was utilized to measure the relevant morphological parameters, and the value of each aesthetic index was calculated according to the formula and morphological parameters. The balance, equilibrium, symmetry, proportion, density, sequence, proportional similarity, unity, and simplicity were represented by $X_1 \sim X_9$, respectively, and the results of each aesthetic index are shown in Table 5.

D. CONSTRUCTION OF THE IMAGE EVALUATION MODEL

Here, taking the "advanced" image in the image cognitive spaces of users and designers as an example, the image evaluation model is established. According to the data in Table 3 and Table 4, quadratic polynomial stepwise regression analysis is carried out. The regression equations used for the image evaluation models of users and designers are fitted by the data processing system (DPS) as follows:

$$\begin{aligned} Y_1 = 3.08 &- 1.44X_4 + 0.19X_5 + 5.49X_7 - 1.48X_1^2 \\ &- 4.62X_5^2 + 2.97X_6^2 - 1.49X_8^2 + 1.27X_9^2 \\ &+ 4.97X_1X_2 - 1.51X_1X_4 - 4.64X_1X_6 \\ &+ 4.38X_1X_7 - 3.13X_2X_5 - 4.29X_2X_6 \\ &- 2.56X_2X_7 + 2.62X_2X_9 + 3.24X_4X_5 \\ &- 1.15X_4X_8 + 4.69X_5X_6 + 2.75X_5X_8 \\ &- 9.60X_7X_9 + 2.31X_8X_9 \end{aligned} \tag{6}$$

$$\begin{aligned} Y_2 = -0.69 &- 0.17X_6 - 0.67X_9 - 1.15X_1^2 - 0.43X_3^2 \\ &- 1.11X_8^2 + 15.28X_9^2 - 4.31X_1X_4 + 3.05X_1X_6 \\ &+ 1.76X_1X_8 + 0.54X_2X_3 + 6.72X_2X_4 \\ &+ 0.96X_2X_5 - 3.46X_3X_6 + 3.95X_3X_8 \\ &- 2.30X_4X_6 + 0.95X_5X_6 + 6.02X_5X_7 \\ &- 14.28X_5X_9 + 1.08X_6X_8 - 4.33X_7X_8 \\ &- 4.10X_7X_9 + 2.74X_8X_9 \end{aligned} \tag{7}$$

where Y_1 and Y_2 represent the "advanced" image evaluation values of users and designers, respectively, and $X_1 \sim X_9$ represent 9 aesthetic indexes.

The regression analysis parameters for (6) are as follows: correlation coefficient $R = 1$, adjusted correlation coefficient $R_a = 1$, $F = 22727.24$, $P = 0.0052$, residual standard deviation $S = 0$, and Dubin-Waston statistic $d = 2.07$. The regression analysis parameters for (7) are as follows: correlation coefficient $R = 1$, adjusted correlation coefficient $R_a = 1$, $F = 22727.24$, $P = 0.0052$, residual standard deviation $S = 0.0001$, and Dubin-Waston statistic $d = 1.42$. Therefore, the two regression equations can correctly reflect the relationship between aesthetic indexes and image cognition, with high reliability and a significant regression effect.

E. NONCOOPERATIVE GAME MODEL BASED ON THE QUANTUM GENETIC ALGORITHM

1) DETERMINATION OF THE DESIGN PARAMETERS

We chose sample 15, with better novelty and moderate complexity, as the optimization design object and determined a total of 11 sphygmomanometer morphological design parameters according to the calculation formula of each aesthetic index, as shown in Fig. 4. The parameter definitions are shown in Table 5.

2) DETERMINATION OF THE PARAMETER RANGE

Based on the minimum and maximum values of each size of the 84 samples, combined with the constraints of the shape and size of sample 15, the value range of each design parameter was determined, as shown in Table 6.

3) ESTABLISHMENT OF THE NONCOOPERATIVE GAME MODEL

The image cognitions of users and designers are regarded as game parties N_1 and N_2, respectively, and the profit functions U_1 and U_2 are represented by (6) and (7), respectively. The strategy space S of all game parties is represented by the 11 morphological parameters in Table 5. The constraint condition is the value range of the morphological parameters in Table 6.

The fuzzy clustering method was used to assign 11 morphological parameters to the strategy set of the game parties:

1) According to (3), the influences of the design variables on the optimization objective are as follows:

$$\begin{aligned} \delta_1 &= (\delta_{11}, \delta_{12}) = (8.09, -0.23) \\ \delta_2 &= (\delta_{21}, \delta_{22}) = (-9.41, 67.77) \\ \delta_3 &= (\delta_{31}, \delta_{32}) = (-13.79, -322.00) \\ \delta_4 &= (\delta_{41}, \delta_{42}) = (-1.18, -71.96) \\ \delta_5 &= (\delta_{51}, \delta_{52}) = (261.83, -30.57) \\ \delta_6 &= (\delta_{61}, \delta_{62}) = (0.12, -22.58) \\ \delta_7 &= (\delta_{71}, \delta_{72}) = (13.48, 314.85) \\ \delta_8 &= (\delta_{81}, \delta_{82}) = (1.41, 86.35) \end{aligned}$$

TABLE 4. Aesthetic index values of 24 sphygmomanometer samples.

Sample	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9
1	0.81	0.98	0.70	0.85	0.90	0.75	0.61	0.67	0.40
2	0.56	0.96	0.67	0.65	0.92	1.00	0.53	0.71	0.25
3	0.88	0.84	0.68	0.95	0.86	1.00	0.63	0.68	0.75
4	0.75	0.99	0.42	0.88	0.52	1.00	0.77	0.35	0.50
5	0.56	0.83	0.77	0.95	0.62	0.50	0.74	0.57	0.50
6	0.50	0.95	0.54	0.88	0.50	1.00	0.62	0.72	0.33
7	0.00	0.95	0.55	0.89	0.78	1.00	0.81	0.89	0.33
8	0.50	0.86	0.56	0.91	0.48	0.50	0.88	0.67	0.50
					…				
24	0.59	0.97	0.62	0.90	0.99	1.00	0.79	0.87	0.60

TABLE 5. Definition table of parameters.

Number	Design parameter	Unit	Number	Design parameter	Unit
1	The horizontal size of the sphygmomanometer D1	mm	7	The horizontal size of the second type of button D4	mm
2	The vertical size of the sphygmomanometer H1	mm	8	The vertical size of the second type of button H4	mm
3	The horizontal size of the screen D2	mm	9	The ordinate of the screen centroid L1	mm
4	The vertical size of the screen H2	mm	10	The ordinate of the centroid of the first type of button L2	mm
5	The horizontal size of the first type of button D3	mm	11	The ordinate of the centroid of the second type of button L3	mm
6	The vertical size of the first type of button H3	mm			

TABLE 6. Value ranges of the design parameters.

Number	Minimum	Value (mm)	Maximum	Value (mm)
1	D1min	84	D1max	130
2	D2min	57	D2max	84
3	D3min	8	D3max	17
4	D4min	12	D4max	33
5	H1min	130	H1max	169
6	H2min	43	H2max	70
7	H3min	9	H3max	17
8	H4min	10	H4min	33
9	L1min	29	L1min	50
10	L2min	1	L2min	28
11	L3min	14	L3min	40

$$\delta_9 = (\delta_{91}, \delta_{92}) = (2.55, -312.08)$$
$$\delta_{10} = (\delta_{101}, \delta_{102}) = (-178.77, 17.76)$$
$$\delta_{11} = (\delta_{111}, \delta_{112}) = (-60.64, -67.49)$$

2) The DPS data processing system was used to perform fuzzy clustering on the above influencing factors, and the clustering results are shown in Fig. 5.

According to the cluster pedigree diagram, taking $\lambda = 0.6$, the 11 design variables can be divided into two categories: $[H_1]$ and $[D_1, D_2, D_3, D_4, H_2, H_3, H_4, L_1, L_2, L_3]$. According to the size of the impact factor and cluster analysis, the strategy set of player N_1 (users) is $S_1 = [H_1]$, and the strategy set of player N_2 (designers) is $S_2 = [D_1, D_2, D_3, D_4, H_2, H_3, H_4, L_1, L_2, L_3]$.

4) RESULTS OF GAME OPTIMIZATION

Using the MATLAB platform, a quantum genetic algorithm was combined with the optimization design program for the sphygmomanometer form. The iteration accuracy was set,

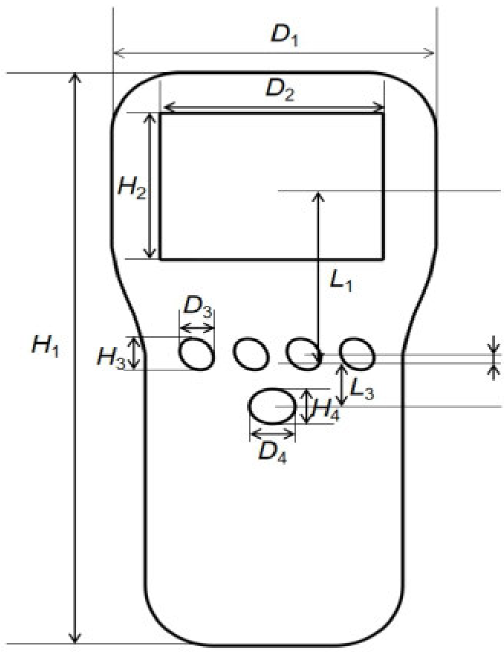


FIGURE 4. Design parameters of the sphygmomanometer.

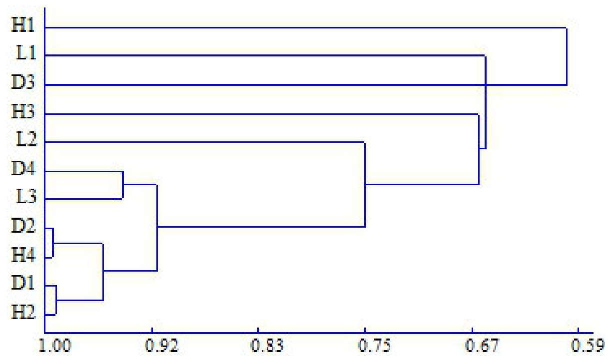


FIGURE 5. Dynamic pedigree diagram of fuzzy cluster analysis.

the program was run, the profit function of each game party was optimized, and it was judged whether the end condition was met. After 34 iterations, the strategy set variable matrix distance reached the accuracy requirements, and the game round ended. Finally, 11 optimized variables were obtained: $H_1 = 168.0$, $D_1 = 90.2$, $D_2 = 70.0$, $D_3 = 11.1$, $D_4 = 18.7$, $H_2 = 68.5$, $H_3 = 13.9$, $H_4 = 11.3$, $L_1 = 31.5$, $L_2 = 22.3$,and $L_3 = 15.7$. The game iteration process of the two profit functions is shown in Fig. 6. After 34 games, the image cognition between users and designers reached a certain equilibrium state. The iterative process of the game with 11 strategy set variables for 2 game parties is shown in Fig. 7. The red and blue curves represent the iterative game process of the first and last two strategy set (S^o and $S^{(1)}$) variables, respectively. The 11 design variables can be seen in the figure. After 34 iterations, the program tends to converge. Finally, the Nash equilibrium solution of the 11 design variables is reached. The comparison between the optimized form scheme and the original scheme is shown in Fig. 8.

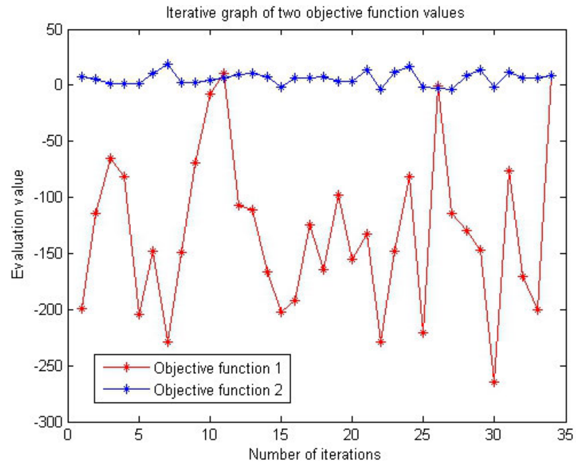


FIGURE 6. Iterative process of the noncooperative game with 2 profit functions.

F. VERIFICATION AND COMPARISON

1) FORM DESIGN BASED ON THE PARTICLE SWARM OPTIMIZATION ALGORITHM

The particle swarm algorithm is a global random search algorithm based on swarm intelligence. Here, Equations (6) and (7) are used as fitness functions, and the particle swarm algorithm is used to construct two sphygmomanometer form evolution design systems. The algorithm program is written in MATLAB. The initial parameters of the two design systems are set as follows: the population number is 50, the learning factors of individuals and groups are both 1.5, the maximum inertia weight is 0.8, the minimum inertia weight is 0.4, and the maximum number of iterations is 500 generations. The optimization iteration process of the two design systems is shown in Fig. 9. The optimized results of the particle swarm algorithm and the proposed method are compared, as shown in Table 7.

Table 7 shows that with the particle swarm algorithm, the image prediction values of users and designers are 4.62 and 6.38, respectively. With the proposed method, the image prediction values of users and designers are 8.79 and 9.04, respectively, which are obviously better than those of the particle swarm optimization algorithm. In addition, using the traditional multiobjective optimization method, sets containing multiple optimization solutions are obtained, and the final design schemes are selected by the decision-maker; this selection is inevitably affected by subjective factors. As an effective tool to solve conflicts between different subjects, game theory is not affected by the weight of either side in the game. It can effectively reflect the subjective initiative and individual rationality in the independent cognitive processes of users and designers, and the optimization results are more objective and reliable. In conclusion, compared with

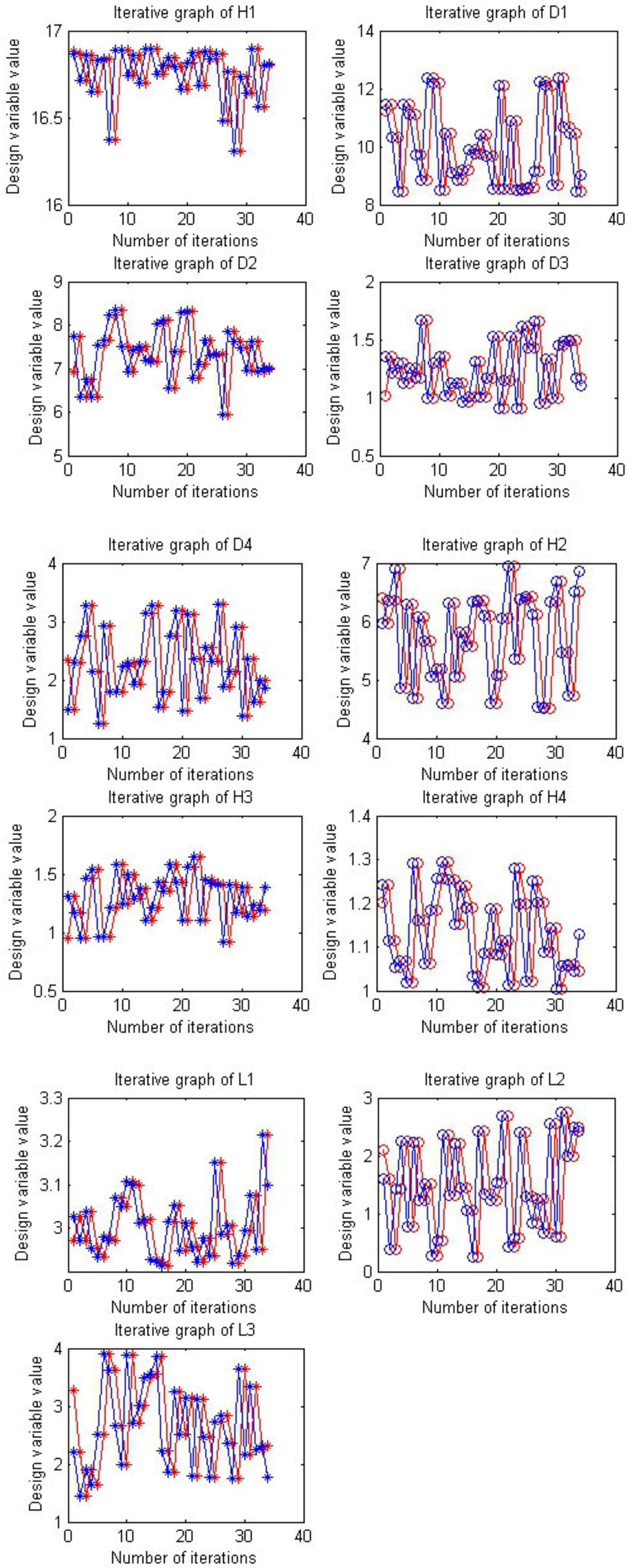


FIGURE 7. Iterative process of the noncooperative game with 11 design variables.

the particle swarm optimization algorithm, this method has obvious advantages.

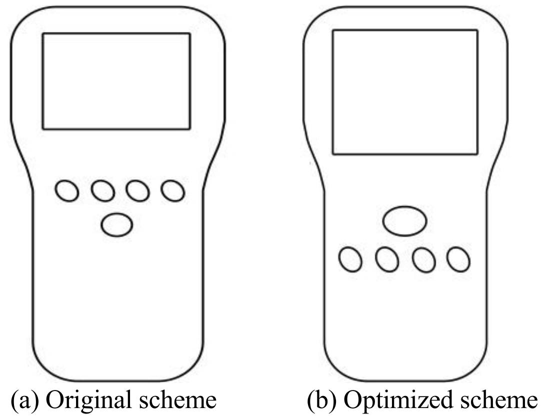


FIGURE 8. Comparison between the original scheme and optimized scheme.

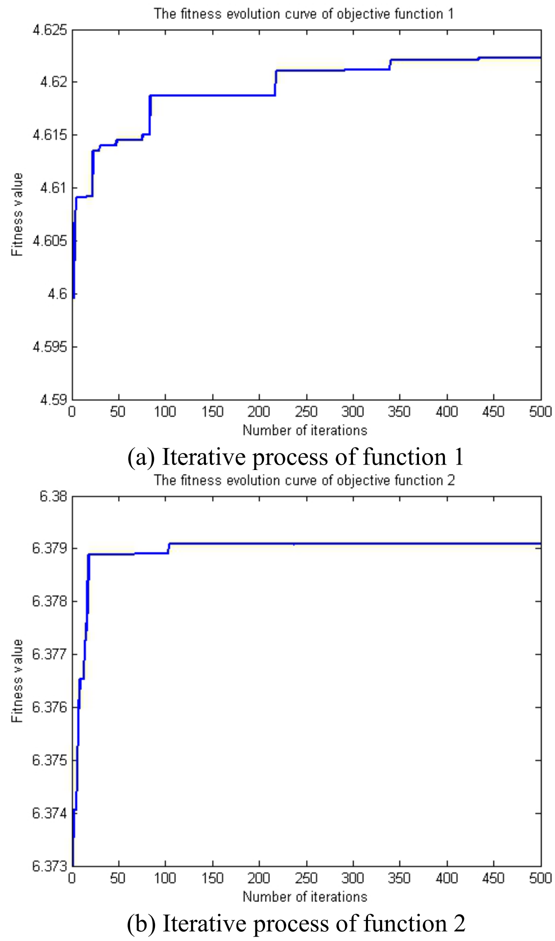


FIGURE 9. Iterative process of the particle swarm algorithm.

2) COMPARISON OF THE SCHEMES

The aesthetic indexes of the original scheme and the optimized scheme are shown in Table 8. The optimized scheme was tested by a questionnaire, and 44 subjects participated in the survey, including 22 users and 22 designers. By observing and analyzing the morphological and layout features of the original scheme and the optimized scheme, the subjects rated the superiority of the two schemes through four distinct aesthetic indexes, balance, symmetry, proportion, and compactness, as well as the "advanced" feature. The score range was [1], [5]. According to the statistical survey results, as shown in Table 9, the optimized scheme performed better in the four dimensions describing the morphological layout of balance, symmetry, proportion, and compactness. In terms of the "advanced" image cognition, the morphological layout of the optimized scheme was better than that of the original scheme. This solution prompts users and designers to view the scheme as more advanced. This proves that this method can effectively balance the cognitions of users and designers and achieve the optimized design of product form.

Comparing the aesthetic indexes of the two schemes in Table 8, the overall width and length of the optimized scheme are larger. The ratio of the overall length to the width is closer to the classical ratio of 0.618, and the ratio is more coordinated. The centroid of the optimized scheme screen moves up, and the centroid of each key moves down; the overall form layout is more in equilibrium. After optimization, the areas of the screen and each key are appropriately increased, the elements in the contour line are arranged more compactly, and the whole scheme looks more harmonious. The length and width of each element are adjusted appropriately, the proportions of the optimized scheme are improved, and the overall elements are arranged more proportionally and neatly. In general, the optimized scheme performs better in most aesthetic indexes. Compared with that of the original scheme, the overall aesthetic is further improved. From the perspective of the image cognitions of users and designers, the "advanced" image value of the optimized scheme is 4.08, while the image value of the original scheme is 3.15. The optimized scheme obtained by this method is better than the original scheme in terms of image and aesthetics.

V. DISCUSSION

In summary, this study is divided into two main parts. One part is the establishment of the image cognition evaluation model, and the other part is the optimization design of the product form. The first part focuses on analyzing the nature of the design cognitive process and exploring the factors that generate cognitive friction between designers and users. According to the aesthetic principles and gestalt principles, we constructed a series of aesthetic indexes that can characterize the aesthetics of product forms, and by exploring the mapping relationship between the aesthetic indexes and the subjects' image cognition, a subject-based image cognitive evaluation model was obtained. The second part focuses on the specific details of applying noncooperative game theory to the optimization design of product form and its implications. In this process, we used the designers' and users' image cognition models as an adaptation function, which can provide a clearer optimization direction for the system, and obtained the product form that is jointly desired by designers and users by simulating the game process of their image cognitions. The structure of the entire system is shown in Fig. 10. In the system, we believe that the difference between the image cognitions of designers and users is the force that continuously drives the iteration and optimization of the product form. The continuous game of cognitive knowledge between designers and users continues to stimulate the optimization system, while the optimization system gives feedback to users and designers, and the two complement each other until the optimal product form is produced.

TABLE 7. Comparison between the optimized results of the particle swarm algorithm and the proposed method.

Methods	Predictive value of image	
	Users	Designers
Particle swarm	4.62	6.38
The method of this paper	8.79	9.04

Computational aesthetics has become an active research area in recent years, where standard design principles are usually extracted and applied as evaluation metrics for the aesthetic assessment of product forms [33]. However, the comprehensiveness of the evaluation indexes in the current research has yet to be improved, and there are few attempts to investigate the complex relationship between human image cognition and aesthetic indexes. In this study, a series of aesthetic metrics were developed based on the relevant aesthetic laws, and the aesthetic calculation of the product form was completed in a more comprehensive manner from different perspectives. The role of each aesthetic index in the aesthetic evaluation processes of different images varies, and there is a complex nonlinear relationship among them. As a multivariate analysis method, quadratic polynomial stepwise regression is able to analyze the complex relationships among influencing factors to predict the results. We used the characteristics of quadratic polynomial stepwise regression to effectively characterize the complex relationship between human image cognition and aesthetic indexes, and we established explicit equations to provide a clearer optimization direction for the subsequent system.

We compare the evaluation method of this paper with the evaluation results of Table 3 in subsection IV-B, as shown in Fig. 11, and the comparative data shown in Table 10. In the image cognitive evaluation model of users, the relative errors of sample 2 and sample 6 are greater than 10%, while the relative errors of the other 22 samples are less than 10%, accounting for 87.5% of the total number of samples; the average relative error of the 24 samples is 7.4%, which is highly reliable. In the image cognitive evaluation model of designers, the relative errors of samples 3, 7, 13 and 22 are greater than 10%, while the relative errors of the other 20 samples are all less than 10%, accounting for 83.3% of the total number of samples; the average relative error of the 24 samples is 9%, which is highly reliable.

TABLE 8. Aesthetic indexes of the two schemes.

Scheme	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9
Original scheme	0.51	0.73	0.82	0.92	0.46	1.00	0.64	0.74	0.67
Optimized scheme	0.54	0.79	0.76	0.93	0.74	1.00	0.82	0.71	0.67

TABLE 9. Results of the questionnaire test.

Scheme	Balance	Symmetry	Proportion	Compactness	Advanced
Original scheme	1.63	1.71	3.19	3.05	3.15
Optimized scheme	4.00	4.14	4.06	4.17	4.08

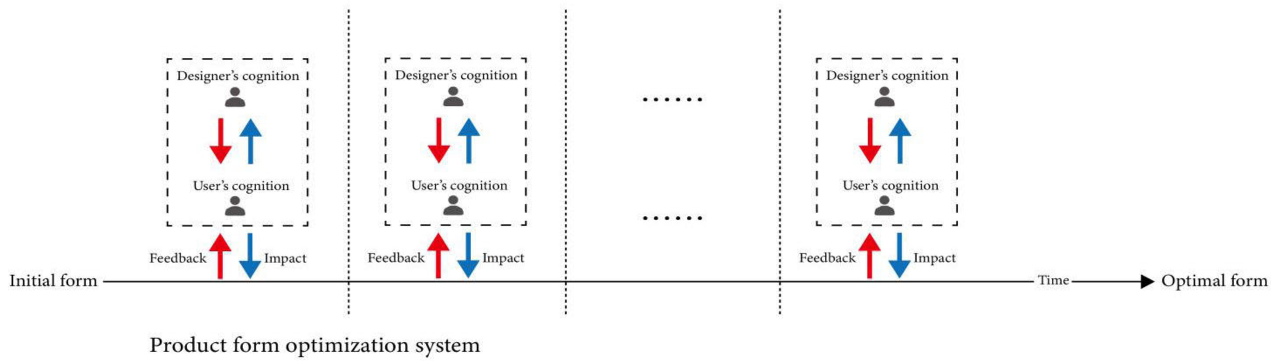


FIGURE 10. The model structure of the overall system.

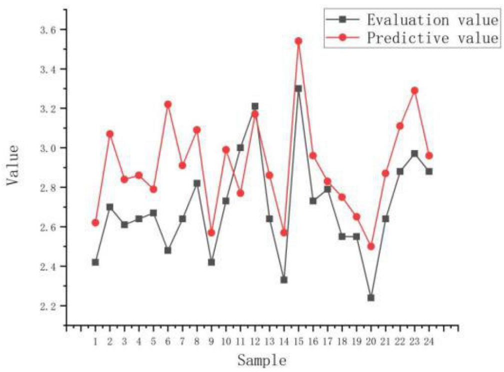
TABLE 10. Comparison of evaluation results.

Sample	User			Designer		
	Evaluation value	Predictive value	Relative error/%	Evaluation value	Predictive value	Relative error/%
1	2.42	2.62	7.6	2.61	2.43	7.4
2	2.70	3.07	12.5	3.06	2.88	6.3
3	2.61	2.84	8	3.12	2.62	19
4	2.64	2.86	7.6	3.15	2.95	6.8
5	2.67	2.79	4.3	3.18	2.96	7.4
6	2.48	3.22	23	3.21	3.05	5.2
7	2.64	2.91	9.3	2.97	2.65	12.1
8	2.82	3.09	8.7	3.18	2.98	6.7
			…			
24	2.88	2.96	2.7	2.94	2.89	1.7

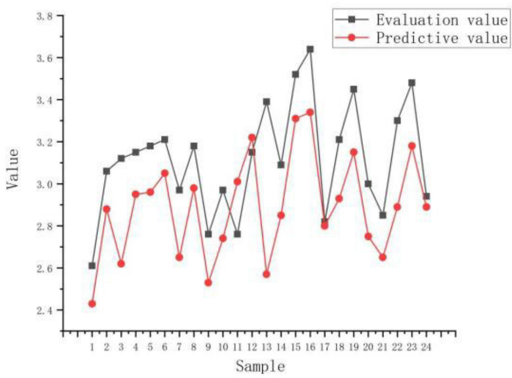
Analysis of the causes of errors: (1) Since human image cognitive evaluation is a perceptual evaluation method, there are factors such as "irrational" decision making, uncertainty, and dynamics, and the random error of the survey results is much larger than that in natural science. (2) The current aesthetic index system is a more comprehensive index system constructed on the basis of existing aesthetic knowledge, which includes the main factors affecting the evaluation of images, but there are also secondary factors. (3) There is insufficient research on the knowledge of aesthetic preferences and the aesthetic thinking structure of evaluation subjects, and it is still difficult to accurately reflect the real

TABLE 11. Performance parameters of different algorithms.

Method	Number of iterations	Time of iterations
Particle swarm	Greater than 200	27s
The method of this paper	34	5s



(a) Users



(b) Designers

FIGURE 11. Comparison of evaluation results.

situation of the aesthetic system through the survey statistics of small samples.

The subject of product form image cognition is human, and image cognition, as an important issue in aesthetics, is an extremely complex mental activity. Due to the constraints of the evaluation subject's experiential knowledge, cultural background, imagination, judgment and other factors, different people may produce different image cognitions at different times and places. In contrast to the cognitive integration approaches for different subjects in [4], we believe that the cognitive integration of designers and users is a dynamic game process and not static. Therefore, we applied noncooperative game theory to simulate this dynamic iterative process and provide a new research idea for the cognitive integration of different subjects. However, there are still some shortcomings of this study. We did not consider other factors that affect the subject's perception of the image in product design, such as color, material & finishing (CMF), usage scenarios and other factors, which may lead to uncertainty in the evaluation system. The next step of our research is to investigate these aspects more deeply.

In this study, the intelligent optimization system of product morphology constructed by combining the quantum genetic algorithm and a noncooperative game can effectively assist designers in using the target product morphology to optimize the solution and bring it closer to the target image of the subject. Compared to the form design method [34], [35], [36], where the morphological curve of the product is expressed parametrically with key points, the design process has many parameters and an enormous workload. Unlike previous methods, we extract the structural design parameters in the product morphology to perform optimization, which decreases the intricacy of the design. Our proposed design system cannot generate variable product forms, but designers can adjust the structural design parameters based on the feedback from the optimization system. In the future, we will focus on the introduction of methods such as sensitivity and variation indexes to screen out design parameters that are important for image cognition.

This method is different from prediction methods such as neural networks and deep learning that require a large amount of data to make predictions. The implementation cost of the design process is relatively low in this study. Unlike neural networks, deep learning and other prediction methods that require a large amount of data and long-term computation, the image cognitive evaluation model does not require a large sample size or computer hardware equipment. To our knowledge, our research is the first to apply game theory to optimize product form. Our work provides a machine learning method for the quantitative image evaluation of product form design patterns and can effectively improve the efficiency of the optimization design of product forms based on the integration of designer and user image cognitions. From the experiment in Section IV-F, it can be seen that the noncooperative game can enhance the optimization results compared with those of the traditional multiobjective optimization algorithm. The relevant performance parameters of the two algorithms are shown in Table 11, and it can be seen from the data in Table 11 that the method in this paper has better performance. In this paper, as a pure strategy-based game method is used, the Nash equilibrium can be found in only a few rounds because of the existence of mutually beneficial solutions between the two sides of the game, and the solution is fast.

Finally, this paper only applies the noncooperative game to optimization design based on the nature of the image cognitive integration process and the similarity of noncooperative game theory, and the exploration of other typical game methods and factors affecting the subject's image cognition will be the focus of our future research.

VI. CONCLUSION

Combined with the theories and methods of Kansei engineering, computational aesthetics and game theory, to address the cognitive friction between users and designers, we proposed an optimization design method for product forms. The SD method was used to complete the image evaluation of the product form by users and designers. Using computational aesthetics methods, the aesthetic index values of the samples were calculated. Utilizing the quadratic polynomial stepwise regression method, two gray-box image evaluation models of design features - aesthetic indexes - images were established. We took the image evaluation models of users and designers as the game side and the two regression models as the profit function. A noncooperative game model based on a quantum genetic algorithm was established, effectively achieving product form optimization design based on the cognitive friction between users and designers; the feasibility of this method was verified through examples.

The proposed optimization design method can effectively integrate emotional factors into the optimization design of product form and explore the problem that the image and aesthetic cognitions of users and designers cannot be comprehensively considered in the current form design. The optimized design scheme generated on this basis meets the common expectations of users and designers and has practical guiding significance for the optimized design of products. It provides a new design method for product form.

With the continuous enrichment of practical human activities, new cognitive knowledge of aesthetics and images will be summarized and developed. In the future, we will continue to upgrade the aesthetic index system of product form, conduct in-depth research on product form design, and further explore the universality and possibility of using this method for the optimization design of product forms. In addition to game theory methods, other methods can be introduced to study the image cognitive friction between users and designers, such as the theory of inventive problem solving (TRIZ), general theory of powerful thinking (OTSM), evidence theory (ET), extension design (ED), and collaborative design (CD). In addition, to meet engineering needs, multiple factors, such as ergonomics, structure, and CMF, can be introduced for integrated design research.

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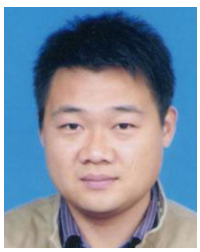

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