www.cadanda.com
Computer-Aided Design AND APPLICATIONS

Optimal Design of Product Form for Aesthetics and Ergonomics

Aimin Zhou[1], Jian Ma[1], Shutao Zhang[1] and Jinyan Ouyang[1]

[1]School of Design Art, Lanzhou University of Technology, 51289547@qq.com; 673223736@qq.com; zhangsht@lut.edu.cn; 250770194@qq.com;

Corresponding author: Shutao Zhang, zhangsht@lut.edu.cn

Abstract. The traditional product form design research usually starts from a single aspect such as aesthetics, ergonomics and Kansei engineering, and lacks the comprehensive consideration of multiple constraints. To solve this problem, a product form optimization design method oriented to aesthetics and ergonomics is proposed. First, based on the theory of computational aesthetics, a quantitative product form aesthetic index system is established. Using the entropy method to achieve the comprehensive evaluation of product form aesthetics. The ergonomic evaluation is carried out by measuring the difference between the standard values and the actual values of the design parameters. Then, taking the aesthetic and ergonomic evaluation as game players, a noncooperative game model is established, and the Nash equilibrium is solved to achieve product form optimization. Finally, We verify by experiments that this method can better realize the multifactor fusion design of the product.

Keywords: aesthetics; ergonomics; multifactor coupling; game theory; product form; optimization design.
DOI: https://doi.org/10.14733/cadaps.2023.1-27

1 INTRODUCTION

As a human-oriented creative activity, product form design involves many factors, such as aesthetics, ergonomics and emotion. With the rapid development of science and technology and the increasing enrichment of material life, users have increasingly higher requirements for products. When making a purchase, users pay attention to not only the practical functions but also the aesthetics of the product. Products with aesthetic appeal provide a good aesthetic experience for users and can produce a pleasant mood. As product form design involves aesthetics, ergonomics, psychology, processing technology and many other fields, traditional product form design research usually starts from a single aspect such as aesthetics, ergonomics and Kansei engineering, which is difficult to meet the multi-dimensional requirements of users for products. Generally, industrial designers prefer vision, because they give products the best shape, material, and color to meet the emotional needs of customers. Engineers pay attention to the performance by adjusting the durability and convenience of products to meet the performance needs of users

[22]. Indeed, product development has become a multifactor decision-making process, and an effective multifactor fusion design method has become the key to product design.

Aesthetic evaluation, as an important issue in aesthetics, is an extremely complex mental activity. Research on the aesthetic evaluation of product form can help designers understand the factors influencing the formation of product aesthetic feelings and the internal relationship and rules of the aesthetic evaluation system. At present, scholars mainly study the aesthetic evaluation of product forms from two perspectives: subjective evaluation and objective evaluation. The subjective aesthetic evaluation mainly uses various survey methods to obtain basic data or subjective weights given by experts, and constructs a comprehensive evaluation model. For example, Zhang et al. used the hierarchical analysis method to construct an aesthetic evaluation system for clothing [31]. Roussos et al obtained data through a survey method and completed an aesthetic evaluation of the product based on the created aesthetic evaluation criteria [18]. Diego et al developed a theoretical framework capable of predicting the emotional response of individual users [4]. The objective evaluation of aesthetics is usually done through computational aesthetics. For example, Birkhoff was the first to try to use standards to measure beauty [1]. Ngo et al. established 13 aesthetic formulas for interface design and completed the aesthetic evaluation of interface design [16]. Since then, after the continuous expansion of research, aesthetic evaluation has achieved many results in different scenarios. For example, Lo et al. used six dimensions of proportion, unity, minimalism, balance, equilibrium, and symmetry to complete the aesthetic evaluation of integrated audio [11]. Hsiao et al. used morphological analysis to determine the morphological characteristics of the coffee machine and established a calculation formula to complete the aesthetic evaluation of the appearance of the coffee machine [8].

In summary, the subjective evaluation method can simply and intuitively reflect the users' perceptions and wishes. The disadvantage is that due to the different evaluation groups, the evaluation process is prone to the phenomenon of too strong subjective preference, resulting in low consistency of evaluation results. Compared with the subjective evaluation method, the aesthetic evaluation from an objective point of view has a strong mathematical theory as the basis, and the method of experiment is clear, the calculation formula is intuitive and the experimental data is precise.

The ergonomic study is a fundamental part of ensuring the comfort and functionality of a product. Good ergonomic design not only avoids work-related musculoskeletal disorders in users, but also improves their efficiency and performance level [25]. The benefits of ergonomic studies at an early stage of the design process are widely recognized. For example, Choi et al determined the location of hard keys on smartphones by statistically analyzing the preferred hard key control areas of users with different hand sizes [3]. Mououdi et al completed an ergonomic design of school bags for elementary school students aged 6-12 years based on anthropometric data [14]. Shankar et al completed an ergonomically optimized design of a blackboard eraser using survey experiments and surface electromyographic sensor experiments [20]. Most of the existing studies on ergonomics have heavy experimental processes and high implementation costs. Ergonomists often have a scientific background and are familiar with the use of numbers and structural drawings, and their findings are often difficult for designers to understand, creating a gap between the field of ergonomics and product design. Therefore, it is particularly important to create an intuitive and effective mathematical model to simplify the ergonomic evaluation process in product design.

Optimal design of product form based on aesthetic and ergonomic factors can be considered as a multi-objective optimization problem (MOP). In the traditional MOP, the weight method is usually used, including the hierarchical sequence method, physical programming method, and weighting method. The MOP is transformed into a single-objective optimization design problem, and then solved and optimized design is realized. For example, Zhu et al. built a comprehensive evaluation model of multiple factors from the perspective of aesthetics, ergonomics, and performance [33]. Kogiso et al. used the weighting method to complete the reliability optimization design of a car body [10]. Zhang et al. used the grey relational theory and weighting method to complete the reliability optimization design of mechanical products [30]. In the above research, a common problem is that the cross-coupling relationship between multiple design objectives cannot be solved. The selection of the weight coefficient or preference function of each objective reflects the subjective consciousness of the designer. The artificial experience is large, and the objectivity of the optimization result is low.

The main contributions of this paper are summarized as follows:

1. Based on the entropy weight method and computational aesthetics theory, we propose a comprehensive aesthetic evaluation model of product form, which overcomes the defects of subjective aesthetic evaluation methods in which weights are sought subjectively and makes the aesthetic evaluation results more objective and reliable.

2. Based on the concept of sensitivity, we introduce it to screen important parameters in the fusion design model for optimal design, which can effectively reduce the workload and complexity of the optimal design.

3. Based on the non-cooperative game theory, we build a non-cooperative game model from the perspective of multi-factor integration design, using the aesthetic evaluation model and the ergonomic evaluation model as two game parties to realize the optimal design of product form. In this model, the aesthetic and ergonomic factors continuously play to generate a driving force to continuously promote the iteration and optimization of the product form. At the same time, the optimization system will also give continuous feedback, the two complement each other until the optimal product form is produced. The intelligent decision system helps designers to optimize the layout of product forms and provides a theoretical basis for intelligent decision-making on product form layout optimization.

The rest of this paper is organized as follows. Section 2 presents the related research methods. In Section 3, we present the detailed process of constructing a multifactor fusion design model. In Section 4, we illustrate the research process of the model with a practical case of a translator. Section 5 demonstrates the discussion of the model. Finally, Section 6 presents some brief conclusions.

2 LITERATURE REVIEW

2.1 Intelligent Design of Product Form

The study of intelligent design of product form is to use an appropriate evaluation model as the fitness function, and then apply intelligent algorithms to assist designers in design decisions to generate product forms that meet users' expectations, commonly used are genetic algorithms, swarm intelligence algorithms, interactive genetic algorithms, hybrid evolutionary algorithms, etc.

Based on this, many scholars have conducted a series of studies. Zhou et al. summarized four formulas for calculating visual balance as an adaptation function of the interface optimization model and applied them to layout adjustment, attribute selection, and scheme optimization of interfaces [36]. Kang et al. constructed a multi-objective optimization mathematical model for the interface element layout based on four indicators of hierarchy, relevance, simplicity and comfort, and used the genetic algorithm to realize the optimal design of product interface layout [9]. Yang et al. constructed a product form evaluation system based on the designer's cognition based on the nonlinear cognitive spider web model proposed by Francisco, and completed the innovative design of the product form by genetic algorithm [29]. Lugo et al. took the contour of a perfume bottle as an example, described it using the Bezier curve, constructed three aesthetic metrics (symmetry, parallelism, and continuity) based on the Gestalt rule, and combined it with a gradient-based optimization algorithm to achieve an optimal design of the perfume bottle form [19].

According to the above, scholars in the field of intelligent design of product morphology are based on different perspectives, respectively. On the one hand, in most of the product form intelligent design studies, the morphological curves of target products are expressed parametrically, key points are extracted to outline the product form, and there are a large number of parameters in the design process with a huge workload. On the other hand, the innovative design of the product form studied only from the perspective of aesthetics may not be able to meet the practicality of the product and the multidimensional needs of users, and the research on the product form design based on several factors is still very scarce, such as engineering factors, ergonomic factors and performance factors.

2.2 Entropy Method

To represent the uniformity of energy distribution in space, the German physicist Rudolf Clausius introduced the concept of entropy in 1856. In 1894, Claude Shannon introduced the concept of entropy to information theory, and expressed the uncertainty of information as an information metric called information entropy. Information entropy can be understood as the degree of information loss. Generally speaking, if the information entropy of a certain index is smaller, it means that the greater the degree of variation of the index, the more information it can provide, and the greater the role it plays in the comprehensive evaluation model, and the greater its weight [37].

The entropy weighting method is based on the differentiated size of the data, and the weight of each index is obtained by the formula of entropy, which is widely used in various fields. Xing et al. proposed an entropy-based surface mesh simplification algorithm that can generate high-quality triangular mesh models quickly and efficiently [27]. Shi et al. improved the weighting accuracy of functional requirement weights in product design by introducing the entropy weighting method [21]. Han et al. used the entropy weight method to calculate the objective weights of each design element to achieve the design of game products [7].

Aesthetic evaluation is a complex multi-indicator decision problem, and its evaluation and decision have an obvious influence on the results of the later stages of design. The early information of product form layout design is ambiguous and incomplete, often determined subjectively by experts based on their professional knowledge and experience, and the aesthetic evaluation of product form layout is an important part of the product development process. Using the entropy weighting method to reduce the subjective factors of decision-makers in assigning weights and obtain objective weights of each index can avoid the subjectivity and randomness of weighting decisions and make the aesthetic evaluation results more objective and reliable.

2.3 Quantum Genetic Algorithm

This is an intelligent optimization algorithm that combines quantum computing and a genetic algorithm. It was proposed by Han et al. It introduced quantum concepts, such as quantum states, quantum gates, quantum state characteristics, and probability amplitudes, into genetic algorithms. Wang et al. applied the quantum genetic algorithm to the field of architecture and optimized the envelope structure of office buildings to minimize construction costs [23]. Zhao et al. Proposed a cognitive radio decision engine based on quantum genetic algorithm, in which the radio parameters are adapted and optimized by quantum genetic algorithm [35].

Compared with the genetic algorithm, the quantum genetic algorithm has three obvious advantages. First, the quantum genetic algorithm uses qubits instead of monotonic binary bits to encode feasible solutions in the solution space; second, the chromosome update operation is increased through the quantum revolving gate instead of using simple crossover and mutation; third, each qubit is an indeterminate state belonging to the superposition state of "0" and "1", which makes the decoding operation different from the encoding operation. Therefore, we use the quantum genetic algorithm to optimize a single objective function to make the convergence speed faster, the optimization ability stronger, maintain the diversity of the population, and finally, achieve a better optimization result.

2.4 Noncooperative Game Model

Game theory is a mathematical method, that is, a decision-making theory to address some kinds of problems with conflict factors. It is mainly used to analyze the behavior between competing individuals. There is no binding agreement between the participants in the game process, and the selection of strategies in the existing strategy space to obtain the optimal strategy under the role of mutual action and constraints is called a non-cooperative game. Chen et al. applied noncooperative theory to the strategy optimization process of the reorganization of used machine tools [2]. Li et al. proposed a turning parameter optimization method based on noncooperative game theory and made a more optimized selection of the turning amount [13]. Lin et al. proposed an optimal planning method for power selling companies based on noncooperative game theory to determine an investment scheme for power generation equipment of power selling companies [12].

In multi-objective optimization problems, the optimization objectives are contradictory and conflicting. The optimization solutions found by various methods have difficulty meeting the needs of each objective. The significance of studying multi-objective optimization problems is to seek one or more solutions so that decision-makers can accept the target value. Game theory mainly analyzes the behaviors of competing individuals in conflict and contradiction environments and studies their optimization strategies. The nature of the optimization problem in this study is very similar to that of the noncooperative game, and the multi-objective optimization mathematical model for ergonomics and morphological aesthetics is transformed into a noncooperative game model.

3 METHODS

A multifactor fusion method for product form optimization design is proposed; its implementation flow is demonstrated in Figure 1.

Step 1: establishing a quantitative system of product form aesthetics indexes based on the laws of formal aesthetics and Gestalt.

Step 2: the aesthetic index value of each sample is obtained based on the aesthetic index formula, and the weight of each aesthetic index is obtained using the entropy weighting method, so a product form aesthetic evaluation model is established.

Step 3: by reviewing relevant literature and books, extracting relevant ergonomic data, determining the standard values of each design parameter, measuring the actual values of the design parameters of the product form, and establishing an ergonomic evaluation model of the product form by measuring the differences between the standard and actual values of each design parameter.

Step 4: sensitivity is introduced to screen out design parameters that have a greater impact on aesthetic and ergonomic factors for optimal design experiments. The multi-objective optimal design problem about product form is transformed into a game decision model and solved by the quantum genetic algorithm to obtain Nash equilibrium to realize the optimal design of the product form layout.

3.1 Experimental Sample Preparation

Images related to the product are collected through the Internet, especially the official website of the product. Based on the principle of covering all essential elements and sample typicality, experts are invited to screen representative samples using the KJ method (also known as the affinity diagram method, which classifies and synthesizes information by analyzing the similarity between them) [15]. Based on the principle of visual perceptual simplification, the morphological elements of each sample are extracted and simplified, and the morphology of the sample is described using the morphological analysis software Rhino 6.0 to obtain the curved graphs of planes as representative samples.

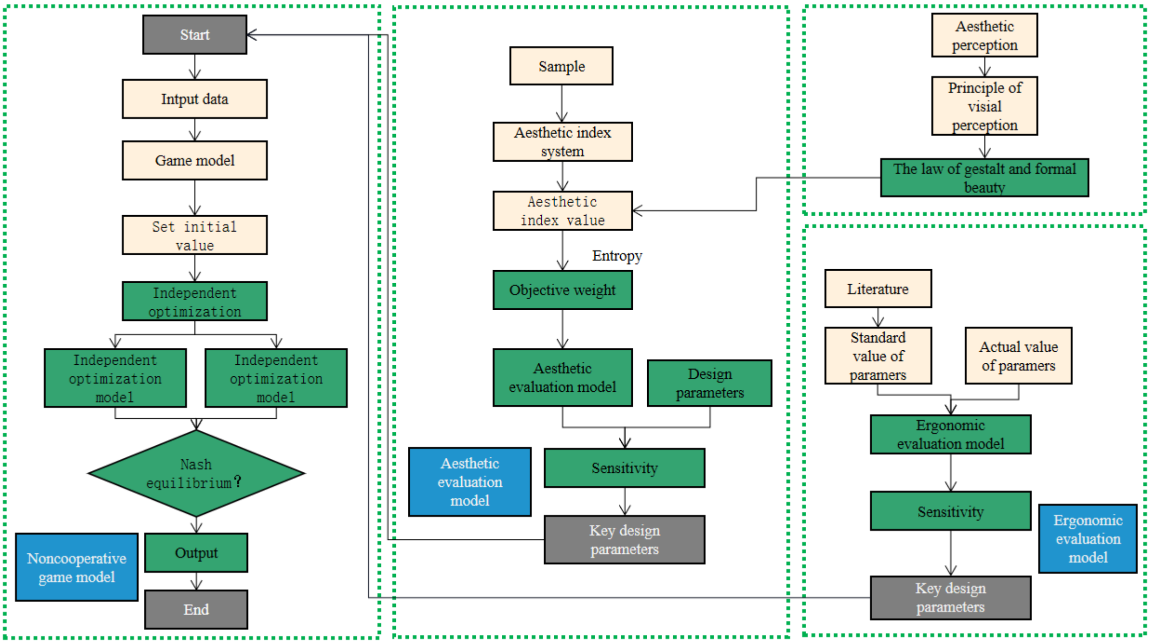


Figure 1: Flowchart.

3.2 Product Form Aesthetic Index System

Based on the laws of formal aesthetics and Gestalt, the aesthetic indexes are used as an index system for the aesthetic evaluation of product form. Since the formula for calculating the aesthetic index can complete the aesthetic calculation of product forms from a quantitative perspective, the implicit aesthetic cognitive knowledge is externalized, and the specific definitions and formulas of each aesthetic index are explained in detail in Table 1 [32]. Therefore, this study introduces it, namely balance (X_1), equilibrium (X_2), symmetry (X_3), proportion (X_4), density (X_5), regularity (X_6), repeatability (X_7), proportion similarity (X_8), unity (X_9), continuity (X_{10}), similarity (X_{11}), simplicity (X_{12}), synchrony (X_{13}), rhythm (X_{14}), sequence (X_{15}).

Definition	*Calculation formula*
Balance (BM): Refers to the stability and balance of the overall arrangement of elements in the layout of the product form, and can measure whether the arrangement of elements in the contour line of the product form and its area size are uniform and reasonable.	$BM = 1 - \frac{\lvert BM_y \rvert + \lvert BM_x \rvert}{2}$; $BM_y = \frac{w_L - w_R}{\max\left(\lvert w_L \rvert, \lvert w_R \rvert\right)}$; $BM_x = \frac{w_T - w_B}{\max\left(\lvert w_T \rvert, \lvert w_B \rvert\right)}$; $w_j = \sum_{i=1}^{n_j} a_{ij} d_{ij}$ *Where BM_y and BM_x are, respectively, the vertical and horizontal balances, a_{ij} is the area of the object i on the side j, d_{ij} is the distance between the centroid c_{ij} and the y-axis, and n_j is the number of objects on the side j. L, R, T and B are representing the left, right, top and bottom quadrants respectively.*

Equilibrium (CDM): The degree of deviation of the center of each element from the center of the smallest external rectangle of the overall contour line.	$$CDM = 1 - \frac{\left\lvert \frac{2\sum_{i=1}^{n} a_i\left(x_i - x_c\right)}{b_f \sum_{i=1}^{n} a_i} \right\rvert + \left\lvert \frac{2\sum_{i=1}^{n} a_i\left(y_i - y_c\right)}{h_f \sum_{i=1}^{n} a_i} \right\rvert}{2}$$ *Where (x_i, y_i) is the coordinate of the center of element i, x_c, y_c are the coordinates of the center of the smallest external rectangle of the overall contour line, b_f is the width of the smallest external rectangle of the overall contour line and h_f is its height.*
Symmetry (SYM): Refers to the degree of overlap of a figure folded on its axis, and the symmetry increases with the degree of overlap.	$$SYM = 1 - \frac{\left(\lvert SYM_y\rvert + \lvert SYM_x\rvert + \lvert SYM_r\rvert\right)}{3}$$ *SYM_y, SYM_x and SYM_r are, respectively, vertical, horizontal and diagonal symmetry. SYM_y can be expressed the following formula. SYM_x and SYM_r are omitted.* $$SYM_y = 1 - \frac{a\left(u_v\right)}{\sum_{i=1}^{n} a_i}\text{;}\ u_v = f_{VRi}\left(x\right) \cup f_{VLi}\left(-x\right)$$ *Where a_i and $a(u_v)$ are, respectively, the areas of the form element i and function curves u_v, $f_{VRi}(x)$ are the curve functions on the right of y-axis, and $f_{VLi}(-x)$ are the mirroring curve functions of the curves on the left of y-axis.*
Proportion (PM): Refers to the proportional beauty of each element and the overall contour line.	$$PM = \frac{\lvert PM_o\rvert + \lvert PM_g\rvert}{2}\text{;}\ PM_o = \frac{1}{n}\sum_{i=1}^{n}\left(1 - 2\min\left(\lvert p_j - p_i\rvert\right)\right)\text{;}$$ $$p_i = \min\left(\frac{h_i}{b_i}, \frac{b_i}{h_i}\right)\text{;}\ PM_g = 1 - 2\min\left(\lvert p_j - p_g\rvert\right)\text{;}\ p_g = \min\left(\frac{h_g}{b_g}, \frac{b_g}{h_g}\right)$$ *Where PM_o is the proportional similarity between the elements and the outer contour of the product form, PM_g is the proportional similarity between the clusters of elements and the outer contour of the product form, b_i is the width of element i, h_i is its height; b_g is the width of the element group and h_g is its height; p_j denotes some classical proportions; for example: (1:1), (1:1.414), (1:1.618), (1:1.732).*
Density (DM): The extent to which the area of the element covers the entire area of the contour line.	$$DM = 1 - 2\left\lvert 0.5 - \left(\sum_{i=1}^{n} a_i\right) / a_o \right\rvert$$
Regularity (RM): Refers to the degree of alignment of the elements within the contour line.	$$RM = \frac{\lvert RM_s\rvert + \lvert RM_c\rvert}{2}\text{;}\ RM_s = 1 - \frac{n_{vs} + n_{hs}}{4n}\text{;}\ RM_c = 1 - \frac{n_{vc} + n_{hc}}{2n}$$ *Where RM_s is the alignment of each element, RM_c is the alignment of the element shape center; n_{vs}, n_{hs} denote the number of tangents in the vertical and horizontal directions for all elements, respectively; n_{vc}, n_{hc} denote the number of tangents in the vertical and horizontal directions over all elemental form centers,*

	respectively.
Repeatability (ECM): The degree of repetition of elements within the contour line of the product form.	$$ECM = 1 - \frac{n_{size}}{n}$$ *Where n_{size} is the number of elements with different morphology.*
Proportion similarity (CSM): Refers to the similarity of the elements and element cluster aspect ratios.	$$CSM = \frac{\left\lvert \min\left(\frac{h_g/b_g}{h_o/b_o}, \frac{h_o/b_o}{h_g/b_g}\right) \right\rvert + \left\lvert \frac{\sum_{i=1}^{n} t_i}{n} \right\rvert}{2};$$ $$t_i = \min\left(\frac{h_i/b_i}{h_o/b_o}, \frac{h_o/b_o}{h_i/b_i}\right)$$ *Where b_o and h_o are, respectively, the width and height of the outline.*
Unity (UM): Unity is the compactness of the form elements.	$$UM = 1 - \frac{a_g - \sum_{i=1}^{n} a_i}{a_o - \sum_{i=1}^{n} a_i}$$ *Where a_o is the area of the product contour line and a_g is the area of the smallest outer rectangle of the element group.*
Continuity (CGM): Refers to the degree to which product forms have visual continuity of clusters.	$$CGM = \frac{n_{ci} - n_{cg}}{2n}$$ *Where n_{ci} is the number of the continuous or coincident lines of the form elements in a certain direction, and n_{cg} is the number of the continuous sets.*
Similarity (SGM): The degree of similarity of elements within the contour line of the product form.	$$SGM = \frac{n_{si} - n_{sg}}{n}$$ *Where n_{si} is the number of the form elements with similar characteristics, and n_{sg} is the number of the similarity sets.*
Simplicity (SUM): The degree of aggregation or simplification of elements into groups within the contour line of the product form.	$$SUM = \frac{n_{sui} - n_{sug}}{n}$$ *Where n_{sui} is the number of the close or connected form elements, and n_{sug} is the number of the simplicity sets.*
Synchrony (CDGM): Refers to the degree of grouping with common directionality between elements within the product form contour line.	$$CDGM = \frac{n_{cdi} - n_{cdg}}{2n}$$ *Where n_{cdi} is the number of the lines with a common direction, and n_{cdg} is the number of the synchrony sets.*
Rhythm (RHM): The degree of regularity of the change of elements within the contour line of the product form.	$$RHM = 1 - \frac{\lvert RHM_x \rvert + \lvert RHM_y \rvert + \lvert RHM_a \rvert}{3};$$ *Where RHM_x and RHM_y are, on the x-axis and y-axis directions respectively, the differences of the centroid positions of the form elements in each*

	quadrant, RHM_a is the difference of the areas of the form elements in each quadrant, and RHM_x can be expressed by the following equations. RHM_y and RHM_a are omitted. $$RHM_x = \left(\lvert X'_{UL} - X'_{UR}\rvert + \lvert X'_{UL} - X'_{LR}\rvert + \lvert X'_{UL} - X'_{LL}\rvert + \lvert X'_{UR} - X'_{LR}\rvert + \lvert X'_{UR} - X'_{LL}\rvert + \lvert X'_{LR} - X'_{LL}\rvert\right)/6;$$ $$X_j = \sum_{i=1}^{n_j} \lvert x_{ij} - x_c\rvert;\ X'_j = \frac{X_j - X_{\min}}{X_{\max} - X_{\min}}$$ *Where x_{ij} is the x-axis coordinate value of the centroid of the form element i in the quadrant j; j=UL, UR, LL, LR, are, respectively, upper-left, upper-right lower-left and lower-right quadrant.*
Sequence (SQM): Refers to the degree to which the order of elements within the contour line follows the general visual observation pattern, generally, upper-left, upper-right, lower-left and lower-right.	$$SQM = 1 - \frac{\sum_{j=UL,UR,LL,LR} \lvert q_j - v_j\rvert}{8};\ v_j = \begin{cases} 4, \text{ if } w_j = \max \text{ in } w \\ 3, \text{ if } w_j = \text{2nd in } w \\ 2, \text{ if } w_j = \text{3rd in } w \\ 1, \text{ if } w_j = \min \text{ in } w \end{cases};$$ $$w_j = q_j \sum_{i=1}^{n_j} a_{ij}$$ *Where qj is the weight value assigned to the four quadrants in the axis based on visual importance, which are 4, 3, 2, 1.*

Table 1: Aesthetic measure of product form layout.

3.3 Comprehensive Evaluation Model of Product Form Aesthetics

The entropy weight method is used to calculate the weight of each aesthetic index. The specific steps are as follows:

Supposing the number of samples is *n*, the number of aesthetic indexes is *m*, and the matrix of aesthetic indexes of each sample is $X = (x_{ij})_{n\times m}$, then standardizing them:

$$x'_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{1}$$

Calculating the information entropy value of each aesthetic index:

$$e_j = -\frac{1}{\ln m}\sum_{i=1}^{m} x'_{ij} \ln x'_{ij} \tag{2}$$

Calculating the information utility value of each aesthetic index:

$$d_j = 1 - e_j \tag{3}$$

Calculating the objective weight of each aesthetic index:

$$W_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \tag{4}$$

According to the above steps, the weights of the aesthetic indexes are determined, and then the evaluation model of the product form aesthetics can be obtained, see equation (5), and the aesthetic evaluation value is calculated by substituting the value of each aesthetic index.

$$N_1 = a_1 X_1 + a_2 X_2 + a_3 X_3 + \cdots + a_m X_m \tag{5}$$

Where, a_1~a_m denote the weight coefficients of each aesthetic index, X_1~X_m denote m aesthetic indexes, and N_1 denotes the aesthetic evaluation value.

3.4 Ergonomic Evaluation of the Product Form

Experienced designers use existing data tools (books, guides, software packages, online resources) to extract ergonomic data during the design process [5]. We extract ergonomic data as standard values by reviewing relevant books and literature, for example, in the ergonomic design of information products, the standard value of key size is based on the size of the 95th percentile bulb of the thumb, and the standard value of the distance between keys is based on the width of the thumb. Scholar Roberts optimized the ergonomic and aesthetic factors of cell phone by interactive genetic algorithm, and his research results showed that for the user's preference, the length and screen area of cell phone type handheld information products are as large as possible, and the width is optimally selected as the middle value within the constraint range, so the length and screen length and width of the translator in this study are selected as the maximum value within the constraint range as its standard value, and the width is selected as the middle value as its standard value [17]. Ergonomic evaluation is usually performed using specific functions or indicators, and ergonomic evaluation is performed by measuring the difference between standard values and actual values [33]. Therefore, this paper determines the standard values of each design parameter based on the ergonomic design standards, conducts the ergonomic evaluation by measuring the differences between the standard and actual values of each design parameter and establishes the relational expressions of the ergonomic evaluation model.

3.5 Multi-factor Fusion Design Model

In order to realize the product form optimization design based on ergonomics and form aesthetics, this study transforms the multi-objective optimization mathematical model for ergonomics and form aesthetics into a noncooperative game decision model named multifactor fusion design model.

3.5.1 Determining the parameters for the optimal design of the product form

The multifactor fusion design model in this paper involves many parameters, and in order to reduce the complexity of the design work, we introduce sensitivity to screen important parameters for optimal design. Sensitivity is the degree of influence of the design parameters on the product performance, small sensitivity parameters can be considered as constant parameters, and large sensitivity parameters can be considered as variable parameters and optimized on the product [24].

We use the first partial derivative method to calculate the sensitivity of each parameter, Supposing the objective function of a certain factor evaluation of the product is $F(x) = \{f_1(x), f_2(x), \cdots, f_E(x)\}$ (E is the number of evaluation factors. In this study, it refers to the ergonomic evaluation and aesthetic evaluation of form), and $x = P^k = \{x_1, x_2, \cdots, x_P\}$ (P is the number of design parameters). The sensitivity of the j-th parameter of a product in the product series to the evaluation value of the i-th factor can be expressed as:

$$M_{ijk} = \frac{\Delta f_i(x)}{\Delta x_j} \tag{6}$$

where Δx_j represents a slight change in the design parameter X, and $\Delta f_i(x)$ represents the resulting change in the evaluation value of the i-th factor.

Equation (7) is the sensitivity matrix of the k-th product, which represents the degree of influence of all design parameters on all evaluation factors.

$$M_k = \begin{bmatrix} \frac{\Delta f_1(x)}{\Delta x_1} & \frac{\Delta f_2(x)}{\Delta x_1} & \cdots & \frac{\Delta f_E(x)}{\Delta x_1} \\ \frac{\Delta f_1(x)}{\Delta x_2} & \frac{\Delta f_2(x)}{\Delta x_2} & \cdots & \frac{\Delta f_E(x)}{\Delta x_2} \\ \vdots & \vdots & \cdots & \vdots \\ \frac{\Delta f_1(x)}{\Delta x_P} & \frac{\Delta f_2(x)}{\Delta x_P} & \cdots & \frac{\Delta f_E(x)}{\Delta x_P} \end{bmatrix} \tag{7}$$

The global sensitivity of the j-th design parameter can be expressed as:

$$M_{Gij} = \frac{\sum_{k=1}^{H} M_{ijk}}{H} \tag{8}$$

where M_{ijk} is the local sensitivity of the j-th design parameter of the k-th product to the i-th evaluation factor, and H is the number of products.

According to the obtained sensitivity, the critical value of the sensitivity is given subjectively [24]. The design parameters with a sensitivity greater than the critical value are determined as the design parameters of form optimization.

3.5.2 Noncooperative game model

Based on the similarity between noncooperative game theory and multi-objective optimization design, the multi-objective optimization mathematical model for ergonomics and form aesthetics is transformed into a noncooperative game decision model. Ergonomics and aesthetics represent two game players N_1 and N_2 respectively. The evaluation function of the two goals of ergonomics and aesthetic optimization can be considered the profit function $\{U_1, U_2\}$ of the corresponding game players. The set of design variables is mapped to the combination of strategy sets of two players, the feasible region of design variables can be considered the feasible space of strategy sets, the design variables are divided into strategy sets belonging to two players by fuzzy clustering analysis: S_1 and S_2. The range of the parameters in the optimization problem is mapped to the constraint condition of game decision making.

In this paper, by calculating the influence factor index of each design variable on each player's profit, and fuzzy clustering the influence factor index, the strategy set belonging to each player is obtained. The specific calculation steps of the classification are as follows:

Step 1: The partial derivative of the design variable X_j with respect to the profit function of the game party is as follows:

$$\delta_j = \left\{ \frac{\partial X_j}{\partial N_1}, \frac{\partial X_j}{\partial N_2} \right\} = \{\delta N_1, \delta N_2\} \tag{9}$$

Step 2: let the clustering object be $\delta_j = \{\delta_{j1}, \delta_{j2}, \cdots, \delta_{ji}, \cdots, \delta_{jm}\}(j = 1,2,\cdots,n)$, δ_j represents the set of influence factors of the j-th design variable on 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: establishing the fuzzy similarity matrix $R=(r_{kl})_{n\times n}$, $0 \le r_{kl} \le 1$, $(k,l = 1,2,\cdots,n)$, r_{kl} represents the degree of association similarity of classification objects (design variables x_k and x_l, that is, clustering objects δ_k and δ_l). There are many ways to calculate r_{kl}, the absolute subtraction is usually used.

$$R=\begin{bmatrix} r_{11},r_{12},\cdots,r_{1l},\cdots,r_{1n} \\ r_{21},r_{22},\cdots,r_{2l},\cdots,r_{2n} \\ \vdots \quad \vdots \quad \cdots \quad \vdots \quad \cdots \quad \vdots \\ r_{k1},r_{k2},\cdots,r_{kl},\cdots,r_{kn} \\ \vdots \quad \vdots \quad \cdots \quad \vdots \quad \cdots \quad \vdots \\ r_{n1},r_{n2},\cdots,r_{nl},\cdots,r_{nn} \end{bmatrix} \tag{10}$$

$$r_{kl}=\begin{cases} 1 & k=l \\ 1-M\sum_{i=1}^{m}\left|\delta_{ki}-\delta_{li}\right| & k\neq l \end{cases} \tag{11}$$

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

Step 4: the transitive closure matrix $t(R)$ of fuzzy similar matrix R can be obtained by using the square automorphism method, and the fuzzy equivalent matrix $\hat{R}=t(R)$ can be obtained. That is, starting from R, we use the square method 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, and $\hat{R}=R^{2^k}$, that is, 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 appropriate confidence level value as $\lambda\in[0,1]$, the matrix is cut according to the level λ of fuzzy equivalent matrix $\hat{R}$, the equivalent relation matrix R_λ is obtained successively. Finally, the different optimal design variables are classified as strategy sets belonging to each player.

3.5.3 Solution of the noncooperative game model

To establish a noncooperative game model and determine the algorithm for solving the Nash equilibrium strategy, the specific steps are as follows:

Step 1: determining the objective function, variables of morphological design, constraint conditions, and iteration accuracy ε;

Step 2: the influence factors of design variables on game players' profit are calculated and fuzzy clustering is performed, strategy sets S_1 and S_2 belonging to each player are obtained;

Step 3: initializing the game analysis and generating the initial strategy set combination $S^o=\{S_1^o,S_2^o\}$ randomly on strategy set space $S=\{S_1,S_2\}$;

Step 4: marking S_{-i}^o as the initial strategy set combination selected by all players except S_i^o in the initial strategy set combination S^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 are combined with a quantum genetic algorithm to perform the corresponding single-objective optimization, that is, for any i-th game player, in its strategy set S_i, find the optimal strategy set S_i^* to maximize the game's profit $U_i\left(S_i^*,S_{-i}^o\right)\to\max$ and meet the constraints of $h_k\left(S_i^*,S_{-i}^o\right)\le 0$, $k=1,2,\cdots,q$ (that is, if there is $U_i\left(S_i^*,S_{-i}^o\right)\ge U_i\left(S_i,S_{-i}^o\right)$, it is called $S^*=\left(S_1^*,S_2^*\right)$ a Nash equilibrium). The flow of the quantum genetic algorithm is shown in Figure 2.

Step 5: supposing $S^{(1)}=S_1^*\cup S_2^*$, calculating whether the distance between the strategy set combination S^o and $S^{(1)}$ before and after meets the convergence criterion $\left\|S^{(1)}-S^o\right\|\le\varepsilon$, where ε is an arbitrarily small positive number. If it is satisfied, the game ends; otherwise replace S^o with $S^{(1)}$, return to step 2 for cyclic calculation, and repeat the iterative calculation until the end condition is met.

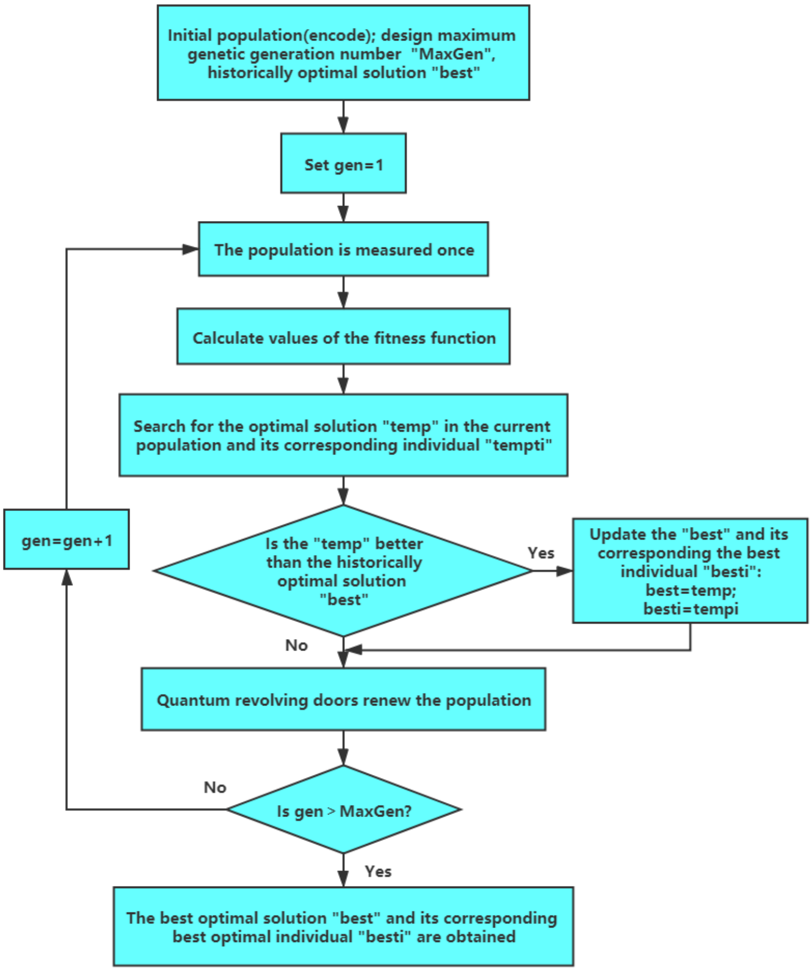


Figure 2: Quantum genetic algorithm flow chart.

In step 4 above, a quantum genetic algorithm needs to be used for optimization. The process of the quantum genetic algorithm is as follows:

Step 1: initializing the population and setting the algorithm parameters (the maximum population number "Maxgen", the historical optimal fitness value "Y_{best}" and its corresponding morphological individual parameter "Y_{besti}"). In this experiment, the fitness functions are the aesthetic evaluation model and the ergonomic evaluation model;

Step 2: setting gen=1;

Step 3: measuring the population once; that is, transform the probability amplitude matrix into a binary matrix;

Step 4: calculating the fitness function value and retaining the optimal fitness value "T" in the current population and the corresponding morphological individual "T_i";

Step 5: determining whether the current optimal solution is better than the historical optimal solution. If so, update the historical optimal solution to $Y_{\mathrm{best}}=T$ and $Y_{\mathrm{besti}}=T_i$; otherwise, enter the next step;

Step 6: updating the population by a quantum revolving gate;

Step 7: increasing the number of iterations by 1 and repeating steps 3-7. When the termination condition is met, the cycle ends;

Step 8: outputting the optimal fitness value "Y_{best}" and the corresponding optimal shape individual "Y_{besti}".

Finally, according to the solution of the noncooperative game model, the value of each optimized design variable is obtained, and Rhino 6.0 is used to establish a model of the optimization plan to complete the optimization design of the product form.

4 EMPIRICAL STUDY

Translators are learning machines for electronic devices that use a computer to realize the conversion of one natural language to another. Translators on the market have abundant forms and are closely related to the operation of human hands. When designing the form, not only the aesthetics of the form must be considered, but also the human-machine operation. Here, the translator is chosen as the research object.

4.1 Experimental Sample Preparation

Ninety samples of translators with different styles are collected through the internet, magazines and journals, which basically covered various styles of translators available in the market. Ten experts are invited to screen the 90 samples using the KJ method to obtain 14 representative samples, as shown in Table 2.

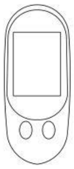
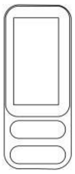
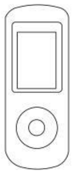
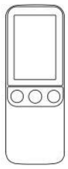
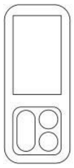
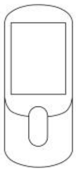
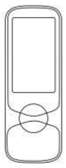
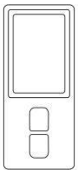
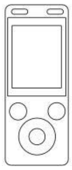
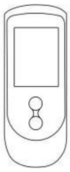
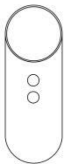
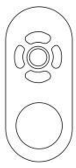
Number	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample							
Number	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Sample							

Table 2: Fourteen morphological samples of translators.

4.2 Calculating the Aesthetic Index

The coordinate system for calculating the aesthetic index is established as shown in Figure 3, where the center of the outer contour of the translator is the origin of the coordinate system, a_i is the area of an element, c_{ij} (x_{ij}, y_{ij}) is the center of the element, and x_{ij}, y_{ij} are the horizontal and vertical coordinates of the center of the element, respectively. According to the principle of visual perceptual simplification, the first-level structures of 14 translator morphological samples are used as the target elements for the calculation of aesthetic indexes, namely, the outer contour, inner screen, outer screen and buttons of the translator. Using the morphological analysis software Rhino 6.0 to measure the relevant aesthetic index data. The balance of the sample in Figure 3 is calculated as an example: The distance from the center of each element to the x-axis and y-axis can be obtained by using the analysis point tool to determine the coordinates of each center; the area of the element above and below the x-axis, and the area of the element to the left and right of the y-axis can be measured by using the area dimensioning tool, and the measured data are brought into the equilibrium formula to obtain the equilibrium value. The values of each aesthetic index for the remaining samples can be obtained sequentially according to the formula in Table 1. Among which the calculated results of order degree and rhythm degree are consistent for 14 samples, which are 1 and 0.333, respectively. These two aesthetic indexes are not distinguished among the 14 morphological samples and are not considered in the aesthetic evaluation experiment, and the calculated results of the other 13 aesthetic indexes are shown in Table 3.

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}
1	0.57	0.93	0.66	0.74	0.66	0.25	0.25	0.83	0.49	0.5	0.25	0.5	0.63
2	0.75	0.95	0.61	0.78	0.34	0.31	0.25	0.71	0.21	0.38	0.75	0.5	0.63
3	0.7	0.8	0.79	0.63	0.96	0.25	0	0.72	0.67	0.75	0.5	0.5	0.5
4	0.54	0.72	0.45	0.81	0.78	0.3	0.2	0.66	0.7	0.6	0.4	0.6	0.5
5	0.53	0.77	0.59	0.64	0.84	0.67	0.33	0.53	0.96	0.58	0.5	0.67	0.58
6	0.70	0.73	0.82	0.58	0.8	0.3	0.2	0.71	0.83	0.7	0.6	0.6	0.7
7	0.62	0.8	0.47	0.87	0.92	0.32	0.25	0.78	0.48	0.75	0.5	0.5	0.88
8	0.49	0.84	0.51	0.93	0.46	0.25	0	0.8	0.28	0.67	0.33	0.67	0.5
9	0.85	0.79	0.89	0.69	0.3	0.25	0	0.73	0.54	0.75	0.25	0.25	0.38
10	0.58	0.85	0.66	0.65	0.74	0.55	0	0.71	0.69	0.4	0.4	0.4	0.8
11	0.95	0.80	0.79	0.36	0.76	0.25	0.25	0.67	0.41	0.69	0.63	0.25	0.63
12	0.55	0.77	0.47	0.69	0.6	0.31	0.25	0.61	0.33	0.5	0.25	0.23	0.63
13	0.75	0.70	0.43	1	0.66	0.31	0.5	0.49	0.51	0.38	0.75	0.5	0.38
14	0.51	0.71	0.93	0.45	0.64	0.54	0.43	0.73	0.6	0.36	0.71	0.57	0.36

Table 3: Aesthetic index values of 14 translator morphological samples.

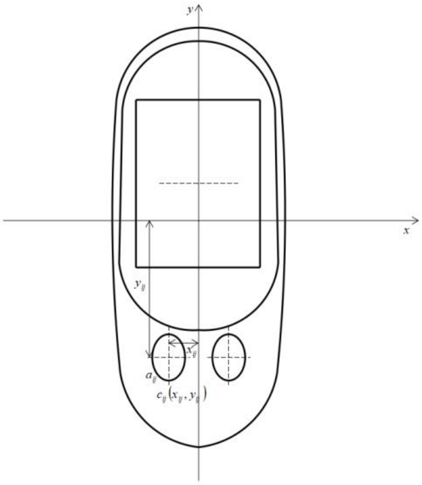


Figure 3: Coordinate chart of the aesthetic index for calculation.

4.3 Comprehensive Evaluation Model of Product Form Aesthetics

The objective weights of the aesthetic indexes are calculated using the entropy weighting method. Based on equations (1) to (4) and Table 3, the objective weights of each aesthetic index are calculated and shown in Table 4.

Aesthetic index	*Objective weight*
X_1	0.0938
X_2	0.1271
X_3	0.0936
X_4	0.1058
X_5	0.1009
X_6	0.0300
X_7	0.0057
X_8	0.1022
X_9	0.0715
X_{10}	0.0722
X_{11}	0.0631
X_{12}	0.0574
X_{13}	0.0767

Table 4: Objective weights of the aesthetic index.

Based on the results of the entropy weighting method, the relational expressions of the comprehensive evaluation model of translator morphology aesthetics are determined by combining the 13 aesthetic indicators and their weights as follows:

$$\begin{aligned} N_1 = {} & 0.0938X_1 + 0.1271X_2 + 0.0936X_3 + 0.1058X_4 + 0.1009X_5 + 0.0300X_6 \\ & + 0.0057X_7 + 0.1022X_8 + 0.0715X_9 + 0.0722X_{10} + 0.0631X_{11} + 0.0574X_{12} \\ & + 0.0767X_{13} \end{aligned} \tag{12}$$

4.4 Ergonomic Evaluation of the Product Form

In this paper, ergonomic data are extracted as standard values by reviewing relevant books and literature. For example, in the ergonomic design of information products, the standard value of key size is obtained based on the size of the 95th percentile thumb bulb muscle, and the standard value of the distance between keys is obtained based on the finger width of the thumb. The standard values of other design parameters are determined according to the literature [17], [28], and the ergonomic evaluation is performed by measuring the difference between the standard and actual values of each design parameter and establishing the relational expressions of the ergonomic evaluation model:

$$N_2 = 1 - \frac{\sum_{i=1}^{p} \frac{\left|q_i - q_j\right|}{q_i}}{p} \tag{13}$$

where q_i is the standard value of a design parameter, q_j is the actual value, p is the number of design parameters to be evaluated, and N_2 denotes the ergonomic evaluation value.

4.5 Multifactor Fusion Design Model

4.5.1 Determining the design parameters of the product form

We choose sample 4 in Table 2 as the sample for the optimization experiment. There are 15 overall design parameters of the translator, as shown in Figure 4, and the parameter definitions are shown in Table 5.

Design parameters	*Unit*	*Design parameters*	*Unit*
The horizontal size of the translator (D_1)	*cm*	*The distance from the centroid of the button to the X-axis (H_4)*	*cm*
The vertical size of the translator (H_1)	*cm*	*The width of the element cluster (D_5)*	*cm*
The horizontal size of the screen (D_2)	*cm*	*The height of the element cluster (H_5)*	*cm*
The vertical size of the screen (H_2)	*cm*	*The area of the button (S_1)*	*cm^2*
The horizontal size of the button (D_3)	*cm*	*The area of the external screen (S_2)*	*cm^2*
The vertical size of the button (H_3)	*cm*	*The area of the inner screen (S_3)*	*cm^2*
The interval between keys (L_1)	*cm*	*The area of overall profile (S_4)*	*cm^2*
The distance from the centroid of the button to the y-axis (D_4)	*cm*		

Table 5: Definition table of parameters.

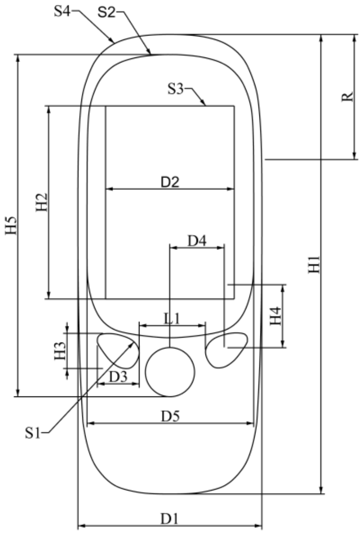


Figure 4: Design parameters of the whole structure of the translator.

4.5.2 Determining parameters for the optimal design of the product form

From Table 2, we select six series of translators with obvious morphological characteristics and individuality: sample (1), sample (2), sample (4), sample (9), sample (12), and sample (13). Rhino 6.0 is used to describe the samples and measure the relevant design parameters. According to equations (6)~(8), the sensitivity indexes of each parameter are calculated, as shown in Table 6.

We subjectively determine the critical value of sensitivity as 0.1. The parameters with sensitivity higher than 0.1 are considered design variable parameters, and other parameters are considered design constant parameters. Finally, we select D_1, D_2, H_1, H_3, H_4, L_1, and S_1 as the optimized design variables.

Design parameter	*Sensitivity*
D_4	0.015
H_4	0.189
D_5	0.055
H_5	0.093
S_1	0.156
S_2	0.008
S_3	0.074
S_4	0.015
D_1	0.390
H_1	0.107
D_2	0.409
H_2	0.070
D_3	0.039
H_3	0.385
L_1	0.214

Table 6: Sensitivity of each design parameter.

4.5.3 Establishing the noncooperative game model

The two design goals of ergonomics and aesthetics are considered two game players N_1 and N_2, respectively. The evaluation function of ergonomics and aesthetics optimization can be considered as the profit function $\{U_1, U_2\}$ of two players, namely equations (12) and (13). The design variable set $X = [D_1, H_1, H_3, L_1]$ shared by two objective functions is mapped to the strategy set combination of two players, and the feasible region of the design variable can be regarded as the feasible space of the strategy set.

Game party strategy set attribution for 4 morphological parameters using fuzzy clustering method. Factor indicators of the impact of each design variable on the profit of each player to the game are calculated by equation (9).

$$\delta_1 = (\delta_{11}, \delta_{12}) = (0.0054, -0.0278) \tag{14}$$

$$\delta_2 = (\delta_{21}, \delta_{22}) = (-2.6355, 0.0100) \tag{15}$$

$$\delta_3 = (\delta_{31}, \delta_{32}) = (0.5843, 0.0833) \tag{16}$$

$$\delta_4 = (\delta_{41}, \delta_{42}) = (8.1653, 0.0500) \tag{17}$$

Then the fuzzy clustering of this influence factor index is taken, as λ =0.8, final set of strategies of two game parties is obtained: $S_1 = \{D_1, L_1\}$, $S_2 = \{H_1, H3\}$.

4.5.4 Setting the parameters of the game model

According to the maximum and minimum sizes of the 90 collected samples, the value range of the morphological parameters is determined, as shown in Table 7.

Parameter	*Value*	*Parameter*	*Value*
D_1min	4cm	D_1max	6cm

D_2min	3.4cm	D_2max	3.9cm
L_1min	1.3cm	L_1max	2.5cm
H_1min	10.7cm	H_1max	12.5cm
H_3min	0.9cm	H_3max	1.5cm
H_4min	2.4cm	H_4max	5.4cm
S_1min	0.74cm^2	S_1max	2.5cm^2

Table 7: Range of design parameters.

4.5.5 Optimal result of the game model

MATLAB is used to program the algorithm, setting the iteration accuracy and then running the program. After a few iterations, the distance of the variable matrix of the strategy set meets the accuracy requirements. At the end of the game round, the four variables of the strategy set after optimization are obtained: $D_1 = 4.97$, $H_3 = 1.47$, $L_1 = 2.17$, and $H_1 = 12.19$. The iterative process of two players with four variables is shown in Figure 5, and the iterative process of two objective functions is shown in Figure 6. The values of other variables are $D_2 = 3.81$, $H_4 = 5.12$, and $S_1 = 2.23$.

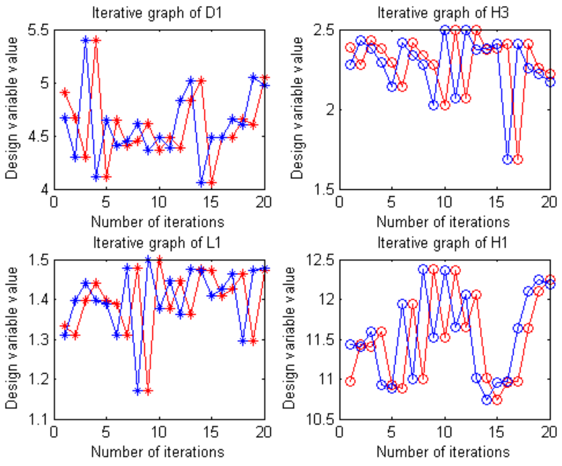


Figure 5: Game iterative process of four design variables.

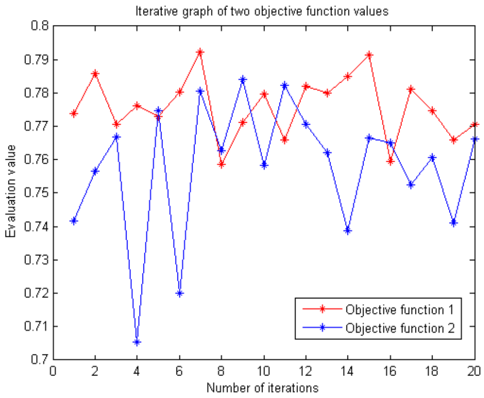


Figure 6: Game iterative process of two objective functions.

Figure 5 shows the game iteration process of each design variable. The red and blue curves represent the game iteration process of the variables of two strategy sets before and after. After 20 iterations of the four design variables, the distance of the matrix of the two strategy sets meets the accuracy requirements. Tending to converge and finally obtaining the Nash equilibrium solution of the four design variables. Figure 6 shows the iterative process of the game with two objective functions. The game ends after 20 rounds. At this time, the two sides of the game have reached a certain equilibrium state.

4.6 Verification and Comparison

4.6.1 Particle swarm algorithm

Particle swarm optimization (PSO) is a swarm intelligence algorithm. Kennedy and Eberhart proposed a global random search algorithm based on swarm intelligence by simulating the migration and clustering behavior of birds in the process of foraging [34]. The experiments in this study are multi-objective optimization problems. To demonstrate the advantages of this study over general optimization algorithms, we introduce a particle swarm optimization algorithm as a comparison for verification.

Numerous scholars have developed applications of particle swarm optimization algorithms in different multi-objective optimization problems to demonstrate their reliability, such as, Zhang et al. used particle swarm optimization algorithm to establish a multi-objective optimization model of vehicle charging and discharging and load scheduling of microgrid to realize load scheduling of microgrid for electric vehicles [38]. Wang et al. combined BP neural network and multi-objective particle swarm algorithm to build an intelligent design model for product imagery modeling, and realized the personalization of product modeling driven by multiple imageries [26]. Because the particle swarm algorithm is effective in solving multi-objective optimization problems, we use it as a benchmark to verify the effectiveness and advantages of the game model in this study.

We set the parameters, write the program in MATLAB and run it. After more than 200 iterations, the algorithm converges. The iterative process of the two objective functions is shown in Figure 7 and Figure 8. The function values obtained by using the particle swarm optimization algorithm are: $N_1 = 0.6208$, $N_2 = 0.6013$.

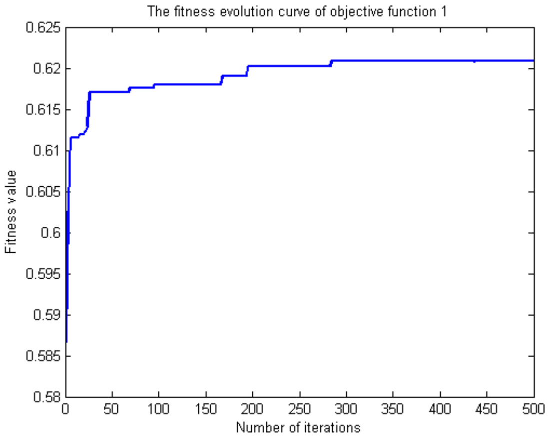


Figure 7: Iterative process of objective function 1.

4.6.2 Comparative analysis of two optimization methods

The values of the objective function and design variable of the two optimization methods are calculated. Table 8 compares the optimization results of the two optimization methods.

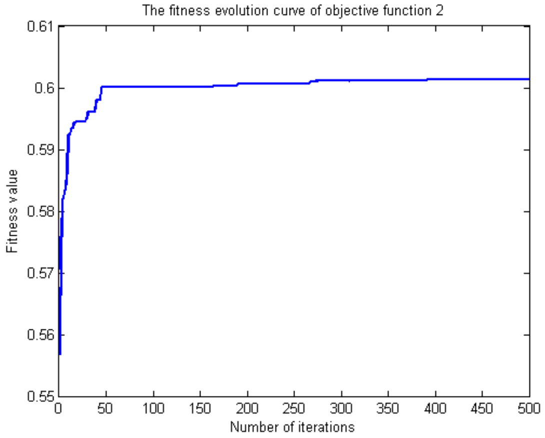


Figure 8: Iterative process of objective function 2.

Method	*Design variable*				*Profit*	
	D_1(cm)	H_1(cm)	H_3(cm)	L_1(cm)	N_1	N_2
Noncooperative game algorithm	4.97	12.19	1.47	2.17	0.7704	0.7662
Particle swarm algorithm	5.91	12.50	1.30	1.29	0.6208	0.6013

Table 8: Results of two optimization methods.

The optimization time and results of our game model are clearly better than those of particle swarm optimization. The programming process of particle swarm optimization is complex, and the iterative process converges slowly. Many parameters need to be set in particle swarm optimization, such as the size of the population, the position, and the speed of each particle. The selection of these parameters usually depends on experience, which makes the design scheme more subjective and less credible. As seen from Table 8, the profits of the two objective functions obtained by PSO are $N_1 = 0.6208$, and $N_2 = 0.6013$, which are clearly lower than those of the game optimization method. The game model we used to analyze and solve the problem is based on the rational point of view, with strong objectivity. In the optimization process, we can optimize multiple objectives at the same time, effectively solve the coupling relationship of multiple objectives in the multi-objective design problem and achieve the equilibrium state between different design objectives. Moreover, the speed of iterative convergence is fast, and the optimization result has good robustness. Therefore, this method can be well applied to the comprehensive optimization of product design.

4.6.3 Analysis and test of the case results

Considering the aesthetics and ergonomics, the model of the optimized scheme and the initial scheme are shown in Figure 9. We use the expert questionnaire method to test the optimization plan. 65 subjects are selected to participate in the experiment, all of whom are researchers in the fields of product design and industrial design, of whom 37 are male and 28 are female. Researchers score the initial plan and the optimized plan based on the sense of balance, symmetry, proportion, density, and comfort of operation.

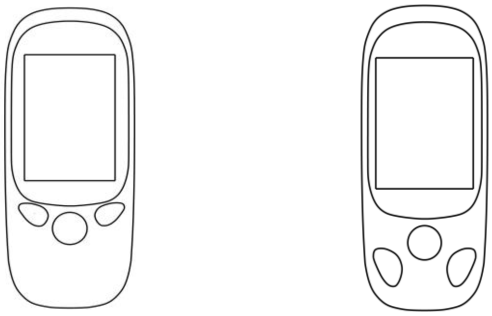


Figure 9: Initial scheme and optimized scheme for sample 4.

The score range is 1-10. The scoring results are shown in Table 9. The performance of the optimization scheme in the five dimensions is better than that of the initial scheme.

The aesthetic differences between the two schemes are as follows: in terms of balance degree, intuitively, after optimization, the arrangement of elements in the whole scheme is more dispersed and the sense of balance is stronger. In the sense of symmetry, the elements of the optimized scheme are arranged more evenly, which enhances the sense of symmetry in the vertical direction of vision. In the sense of proportion, the ratio of the waist to the bottom of the isosceles triangle formed by the three-button centroids is 0.621, which is near the golden ratio of 0.618. The ratio of the bottom of the isosceles triangle formed by the three-button centroids to the overall width is 0.605, which is near the classic ratio of 0.618. The elements are evenly arranged and have a ratio near the classical value, so a good aesthetic feeling is presented. In terms of density, the density of the optimization scheme is closer to 0.5, and the whole is more harmonious. However, in the initial scheme, the arrangement of elements is relatively concentrated, and no proportion is near the classic value, so the aesthetic feeling is poor.

The differences in operation between the two schemes are as follows: The visual organization of the elements in the optimization scheme is orderly, the size and distance of the buttons are increased compared with the original scheme, and the contour width of the optimization scheme is reduced, which is more suitable for grasping and more comfortable to operate.

Evaluation indicators	*Sample 4*		*Sample 5*		*Sample 9*	
	Initial plan	*Optimized plan*	*Initial plan*	*Optimized plan*	*Initial plan*	*Optimized plan*
Balance	*5.65*	*7.55*	*3.50*	*9.10*	*6.65*	*8.50*
Symmetry	*7.60*	*7.95*	*5.60*	*8.50*	*5.50*	*6.65*
Proportion	*6.10*	*7.30*	*3.65*	*7.30*	*6.30*	*8.10*
Density	*4.65*	*7.25*	*3.00*	*9.50*	*6.10*	*8.80*
Comfortability	*5.05*	*7.00*	*4.50*	*8.65*	*5.25*	*9.10*
Comprehensive	*5.81*	*7.41*	*4.05*	*8.80*	*5.96*	*8.23*

Table 9: Results of expert questionnaire.

In addition, since the ratio of the combined scores of the sample 4 in Table 9 is 7.41/5.81=1.2753... The ratio is not high, and the above morphological optimization experiment is repeated for sample 5 and sample 9 in Table 2, and the optimized solution and the initial solution for sample 5 are shown in Figure 10, the optimized solution and the initial solution for sample 9 are shown in Figure 11. The tests are also conducted using the expert questionnaire method, and the results of the scores for sample 5 and sample 9 are shown in Table 9.

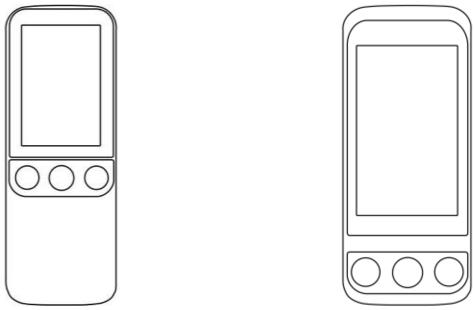


Figure 10: Initial scheme and optimized scheme for sample 5.

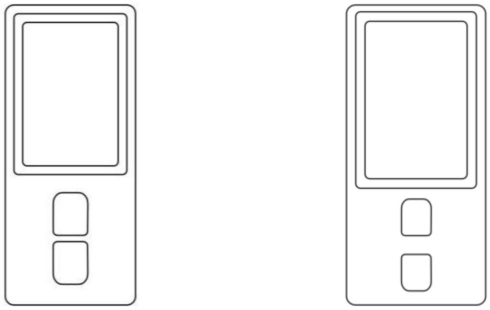


Figure 11: Initial scheme and optimized scheme for sample 9.

According to Table 9, the optimized solution of sample 5 outperformed the initial solution in all five dimensions, the whole program is more scattered and balanced after the optimization, and the elements are more evenly arranged after the optimization, giving a sense of symmetry in the vertical direction and a more harmonious overall, and the ratio of their comprehensive scores is 8.80/4.05=2.1728. The optimized sample 9 also had a greater advantage in all dimensions, after optimization, the whole program is more balanced, with an enhanced sense of symmetry and more harmonious overall, and the distance between the screen and the keys is increased, making the operation process more comfortable. and the ratio of their comprehensive scores is 8.23/5.96=1.3808. Thus, the effectiveness of the method of this paper is verified.

5 DISCUSSION

In summary, the work of this study is divided into two main parts. One is the establishment of the multifactor evaluation model, and the other is the introduction of the noncooperative game theory to realize the multifactor fusion design of product form. In the first part, we focus on the details of the evaluation model. The second part focuses on the specific details of the application of noncooperative game theory to the multifactor fusion design and its significance.

The ergonomic model in this study is based on static human characteristics data for evaluation, which has the advantage of being able to communicate this information to the designer in a simple and intuitive way. However, it cannot consider a series of dynamic postures that are closely related to the human movement process, which reduces the accuracy and reliability of ergonomic evaluation to a certain extent.

Traditionally, methods for solving multi-objective optimization problems have problems such as high computational effort and poor convergence [6], typically represented by multi-objective genetic algorithms. Based on the similarity between multi-objective optimization design and the noncooperative game theory, this study introduces the noncooperative game theory into the process of product form optimization design by combining its strong advantages and robustness in solving multi-objective optimization problems. To the best of our knowledge, our research is the first attempt to apply game theory to the optimization design of product form, and the comparative analysis in subsection 4.6.4 of this paper shows that it can effectively improve the optimization results and make the optimization results more objective and reliable.

In this study, the design decision process can be carried out in a computer environment, which is conducive to the realization of intelligent design. Unlike prediction methods such as neural networks and deep learning, which require a large database to achieve the expected effect of the experiment with a high probability, the evaluation model constructed in this paper does not require a high sample size and computer hardware equipment, and can reflect the basic situation of the model with a moderate amount of samples, which reduces the implementation cost to a certain extent.

Finally, in this paper, we only apply the noncooperative game to optimal design, and the exploration of other typical game methods and more efficient fusion design methods will be the focus in our future research.

6 CONCLUSIONS

We propose a multifactor fusion design method of product form based on the noncooperative game theory. First, evaluation methods are established for the determined multiple design factors. In terms of aesthetic evaluation, we established a aesthetic evaluation model based on the theory of computational aesthetics and entropy method, which can serve the defects of subjective evaluation methods in which weights are sought subjectively and make the aesthetic evaluation results more objective. Second, we introduce the sensitivity to distinguish many parameters involved in product series design to reduce the number of parameters to be optimized, which can effectively improve the product development speed of enterprises. Finally, based on the similarity between the multi-objective optimization design and the noncooperative game theory, we consider the ergonomic evaluation function and the aesthetic evaluation function as two game players. We establish a noncooperative game model, which can effectively realize the equilibrium between product design ergonomics and aesthetics and effectively solve the coupling relationship between multiple objectives in multi-objective design. The model is more objective. Finally, the validity of the model is verified by comparing it with other algorithms.

With the development of science and technology, product design pays more and more attention to aesthetics, engineering and other comprehensive factors. This paper can help designers grasp the design process more accurately by establishing a quantitative evaluation method for aesthetic and ergonomic factors, and the introduction of noncooperative game theory largely balances the aesthetic and ergonomic factors in product design, providing a new and effective method for the multifactor fusion design of products. In this study, only the product form is taken as the object of study, and other factors that influence the design process, such as CMF (Color, Material & Finishing), usage scenarios, are not considered. In the future, it will be the focus of our research to build a convergent design model that integrates more factors.

7 ACKNOWLEDGEMENTS

This research is funded by the National Natural Science Foundation of China (grant no. 51705226), the Natural Science Foundation of Gansu Province (grant no. 20JR10RA168) and the Innovation Fund Project of Colleges and Universities in Gansu Province (grant no. 2021A-020).

Aimin Zhou, http://orcid.org/0000-0002-3994-9040
Jian Ma, https://orcid.org/0000-0003-2237-8103
Shutao Zhang, https://orcid.org/0000-0003-4665-5443
Jinyan Ouyang, https://orcid.org/0000-0003-4165-8573

REFERENCES

[1] Birkhoff, G.-D.: Aesthetic Measure, Massachusetts Harvard University Press, New York, NY, 1933. https://xueshu.baidu.com/usercenter/paper/show?paperid=ac628a3aa5ca1709b3d315a32aaece0a&site=xueshu_se

[2] Chen, Y.-S.; Jiang, Z.-G.; Zhu, S.; Zhang, H.: Research on reassembly strategy of used mechanical equipment components based on non-cooperative game, Journal of Mechanical Engineering, 57(9), 2021, 203-212. http://www.cjmenet.com.cn/CN/10.3901/JME.2021.09.203

[3] Choi, Y.-C.; Yang, X.-P.; PARK, J.-W; Jung, H.: Development of an ergonomic design process for smartphone hard key locations, Applied Ergonomics, 97, 2021. https://doi.org/10.1016/j.apergo.2021.103532

[4] Diego-Mas, J.-A.; Alcaide-Marzal, J.: Single users' affective responses models for product form design, International Journal of Industrial Ergonomics, 53, 2016, 102-114. https://doi.org/10.1016/j.ergon.2015.11.005

[5] Eldar, R.; Fisher-Gewirtzman, D.: Ergonomic design visualization mapping- developing an assistive model for design activities, International Journal of Industrial Ergonomics, 74, 2019. https://doi.org/10.1016/j.ergon.2019.102859

[6] Feng, J.-Z.; Zhang, J.-G.; Qiu, J.-W.: Game algorithm for reliability multi-objective design optimization based on adaptive behavior, Computer Integrated Manufacturing Systems, 25(3), 2019, 736-742. http://cims-journal.cn/CN/10.13196/j.cims.2019.03.020

[7] Han, X.; Li, Y. -X.; Tan, B. -H.; Yu, Y.; Tu, X. -X.: Research on product design based on fuzzy kano model and entropy weight TOPSIS, 2022, 1-13. https://kns.cnki.net/kcms/detail/detail.aspx?dbcode=CJFQ&dbname=CAPJLAST&filename=BZGC20211112005&v=MzAwNzFsVkwvSklGYz1KemZNYmJHNEhORE5ybzVIWk9zS1l3OU16bVJuNmo1N1QzZmxxV00wQ0xMN1I3cWRaZVpyRml2

[8] Hsiao, S.-W.; Chiu, F.-Y.; Lu, S.-H.: Product-form design model based on genetic algorithms, International Journal of Industrial Ergonomics, 40(3), 2010, 237-246. https://doi.org/10.1016/j.ergon.2010.01.009

[9] Kang, H.; Yang, S. -X.; Deng, S. W.; Wang, B.: Multi-objective optimization design of product operation interface element layout, Packaging Engineering, 41(8), 2020, 149-153+172. https://kns.cnki.net/kcms/detail/detail.aspx?dbcode=CJFQ&dbname=CJFDLAST2020&filename=BZGC202008028&v=MTgzMzBoMVQzcVRyV00xRnJDVVI3aWZZK1p0Rnl6a1VyM0JKemZNYmJHNEhOSE1wNDlIYklSOGVYMUx1eFlTN0Q=

[10] Kogiso, N.; Kodama, R.; Toyoda, M.: Reliability-based multiobjective optimization using the satisficing trade-off method, Mechanical Engineering Journal, 1(6), 2014. https://doi.org/10.1299/mej.2014dsm0063

[11] Lo, C.-H.; Ko, Y.-C.; Hsiao, S.-W.: A study that applies aesthetic theory and genetic algorithms to product form optimization, Advanced Engineering Informatics, 29(3), 2015, 662-679. https://doi.org/10.1016/j.aei.2015.06.004

[12] Lin, K.-J.; Wu, J.-Y.; Hao, L.-L; Liu, D.: Optimization of operation strategy for micro-energy grid with CCHP systems based on non-cooperative game, Electric Power Automation Equipment, 42(6), 2018, 25-32. http://qikan.cqvip.com/Qikan/Search/Index?from=Qikan_Article_Detail

[13] Li, C.-Y.; Wu, Z.-J.; Gan, Y.; Yang, L.-H.; Cao, Y.-L.: Turning parameters optimization selection method based on non-cooperative, Computer Integrated Manufacturing Systems, 26(11), 2020, 3020-3030. http://cims-journal.cn/CN/10.13196/j.cims.2020.11.012

[14] Mououdi, M.-A.; Albari, J.; Mousavinasab, S.-N.: Ergonomic design of school backpack by using anthropometric measurements for primary school students (6 - 12 years), International Journal of Industrial Ergonomics, 67, 2018, 98-103. https://doi.org/10.1016/j.ergon.2018.05.001

[15] Mu, Y.; Zhang, J.-X.; Wang, A.-Q.; Li, M.: Design research on trench coat product based on KJ-Technique and Kano analysis, Wool Textile Journal, 48(5), 2020, 42-48. http://www.cqvip.com/QK/94636X/202005/7101728341.html
[16] Ngo, D.-C.-L.; Teo, L.-S.; Byrne, J.-G.; Li, M.: Modelling interface aesthetics, Information Sciences, 152, 2003, 25-46. https://doi.org/10.1016/S0020-0255(02)00404-8
[17] Nathan-Roberts, D.; Liu, Y.: Investigation of Relative Mobile Phone Size Preference Using Interactive Genetic Algorithms, 54th Annual Meeting of the Human Factors and Ergonomics Society, San Francisco, California, 2010, 1807-1811. https://www.researchgate.net/publication/315071335_Investigation_of_Relative_Mobile_Phone_Size_Preference_Using_Interactive_Genetic_Algorithms
[18] Roussos, L.; Dentsoras, A.-J.: Formulation and use of criteria for the evaluation of aesthetic attributes of products in engineering design, 19th International Conference on Engineering Design (ICED13), Design for Harmonies, 2013. https://www.designsociety.org/publication/34619/Formulation+and+use+of+criteria+for+the+evaluation+of+aesthetic+attributes+of+products+in+engineering+design
[19] Romero, A.-V.; Lugo, J.-E.: Part-worth utilities of gestalt principles for product esthetics: a case study of a bottle silhouette, Journal of Mechanical Design, 138(8), 2016. https://doi.org/10.1115/1.4033664
[20] Shankar, S.; Naveen, K.-R.; Janaki, R.-S.; Hariharan, C.-P.-S.: Ergonomic evaluation of ergonomically designed chalkboard erasers on shoulder and hand-arm muscle activity among college professors, International Journal of Industrial Ergonomics, 84(4), 2021. https://doi.org/10.1016/j.ergon.2021.103170
[21] Shi, Y.; Peng, Q.; Zhang, J.: An objective weighting method of function requirements for product design using information entropy, Computer-Aided Design and Applications, 17(5), 2019. https://xs.dailyheadlines.cc/scholar?hl=zh-CN&as_sdt=0%2C5&q=An+objective+weighting+method+of+function+requirements+for+product+design+using+information+entropy&btnG=
[22] Wang, Y.; Tseng, M.-M.: Integrating comprehensive customer requirements into product design, CIRP Annals-Manufacturing Technology, 60(1), 2011, 175-178. https://doi.org/10.1016/j.cirp.2011.03.091
[23] Wang, Y.; Wei, C.: Design optimization of office building envelope based on quantum genetic algorithm for energy conservation, Journal of Building Engineering, 35, 2020. https://doi.org/10.1016/j.jobe.2020.102048
[24] Wei, W.; Ji, J.; Wuest, T.; Fei, T.: Product Family Flexible Design Method Based on Dynamic Requirements Uncertainty Analysis, Procedia CIRP, 60, 2016, 332-337. https://doi.org/10.1016/j.procir.2017.01.037
[25] Wang, J.; Han, S.; Li, X.: 3D fuzzy ergonomic analysis for rapid workplace design and modification in construction, Automation in Construction, 123, 2021. https://doi.org/10.1016/j.autcon.2020.103521
[26] Wang, P.; Zhang, W.; Bai, R.-S.: Research on product image personalization customization system driven by multi-image, Computer Technology and Automation, 40(1), 2021, 7-14. http://qikan.cqvip.com/Qikan/Article/Detail?id=7104213888
[27] Xing, L.-P.; Hui, K.-C.: Entropy-based mesh simplification, Computer-Aided Design and Applications, 7(6), 2010, 911-918. https://www.tandfonline.com/action/doSearch?AllField=Entropy-based+mesh+simplification&SeriesKey=tcad20
[28] Yang, G.; Liu, J.-H.; Yang, X.-N.; Chen, Z.-B.; Fang, J.-G.: Ergonomics Based on Information Products, Tsinghua University Press, China, Beijing, 2015.
[29] Yang, W.; Su, J. -N.; Zhang, S.; Qiu, K.; Zhang, X. -X.: Intelligent design of product forms based on design cognitive dynamics and a cobweb structure, Computational intelligence and neuroscience, 2021: 6654717. https://www.researchgate.net/publication/349235490_Intelligent_Design_of_Product_Forms_Based_on_Design_Cognitive_Dynamics_and_a_Cobweb_Structure

[30] Zhang, R.-J.; Qiu, J.-W.; Jia, Q.-X.: Multi-objective robust design for reliability based on grey system theory, Journal of Beijing University of Posts and Telecommunications, 37(3), 2014, 23-26+42. http://qikan.cqvip.com/Qikan/Article/Detail?id=662183823
[31] Zhang, Y.-Z.; Zhang, J.-S.: Weight calculation of appeal aesthetics evaluation dimension based on AHP, Wool Textile Journal, 47(5), 2019, 81-85. http://qikan.cqvip.com/Qikan/Article/Detail?id=7002063442
[32] Zhou, A.-M.; Ouyang, J.-Y.; Su, J.-N.; Zhang, S.-T.; Yan, S.-T.: Multimodal optimisation design of product forms based on aesthetic evaluation, International Journal of Arts and Technology, 12, 2020, 128-154. https://www.researchgate.net/publication/343145821_Multimodal_optimisation_design_of_product_forms_based_on_aesthetic_evaluation
[33] Zhu, S.-Y.; Hu, J.; Qi, J.: Multi-factor coupling design based on aesthetic measure, ergonomics, and performance, Journal of Mechanical Engineering, 56(21), 2020, 199-207. http://www.cjmenet.com.cn/CN/10.3901/JME.2020.21.199
[34] Zhou, J.-M.; Zhang, L.-X.; Yi, F.-Y.; Peng, J.-K.: Adaptive cruise predictive control based on particle swarm optimization, Transactions of Beijing Institute of Technology, 41(2), 2021, 214-220. http://journal.bit.edu.cn/zr/ch/reader/key_query.aspx
[35] Zhao, Z.-J.; Zheng, S.-L.; Shang, J.-n.; Kong, X.-Z.: A study of cognitive radio decision engine based on quantum genetic algorithm, Acta Physica Sinica, 56(11), 2007, 6760-6766. https://www.researchgate.net/publication/291986404_Study_of_cognitive_radio_decision_engine_based_on_quantum_genetic_algorithm
[36] Zhou, L.; XUE, C. -Q.; Tomimatsu, K.: Research of interface composition design optimization based on visual balance, Advances in Intelligent Systems & Computing, 279, 2014, 483-493. https://link.springer.com/chapter/10.1007/978-3-642-54927-4_46
[37] Zhang, Y. -L.; Dong, Z. -A.; An, H. -G.: Neural network optimization algorithm in the field of techno-economic applications, Metallurgical Industry Press, Beijing, 2015.
[38] Zhang, X.; Wang, Z.; Lu Z.: Multi-objective load dispatch for microgrid with electric vehicles using modified gravitational search and particle swarm optimization algorithm. Applied Energy, 2022, 306. https://www.sciencedirect.com/science/article/pii/S0306261921013180