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# Research on the Optimization Method of Intelligent Product Design by Integrating Cognitive Science and Machine Vision Technology

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**Abstract** Smart product design needs to take into account both functionality and aesthetic needs, and traditional design methods are difficult to balance these multidimensional goals. This study integrates cognitive science and machine vision technology to construct an intelligent product design optimization method. In the method, user needs and aesthetic forms are regarded as complex adaptive systems, Gray coding is used to encode product features, a multi-objective optimization model is constructed based on NSGA-II algorithm, and the optimal design scheme is selected through non-dominated sorting and congestion calculation. The experimental design invites 30 designers to participate and provides three types of external incentives, namely, far-domain incentives, near-domain incentives and constraints. The results show that the far-field incentive group generates an average of 3.61±1.73 number of solutions in the design stimulus phase, which is significantly higher than the 2.5±1.52 of the near-field incentive group and the 2.44±1.47 of the constraints group. In the evaluation of the importance of technological attributes, the TA2 proximity coefficient reaches 0.6473, which is the second highest, while the proximity coefficients of TA8 and TA14 are both 0.0001. It shows that the impact of different technical attributes on user satisfaction varies significantly. The study shows that the design optimization method integrating cognitive science and machine vision can effectively improve the usability of intelligent products, resolve technical conflicts, and realize the innovative design of products oriented to user needs.

**Index Terms** cognitive science, machine vision technology, complex adaptive system, NSGA-II algorithm, user needs, product innovation design

## I. Introduction

How to make products maintain competitive advantage in the market for a long time is a problem that enterprises need to think about at the product design level. Each product has its life cycle, the product's sales time is long, there may be function aging, old appearance and other problems, can not meet the current market trends and consumer demand, and the way to get rid of this dilemma is to upgrade the product [1]-[4]. Through upgrading and iteration, product structure, appearance and shape, functional innovation and other aspects of optimization design [5]. Product design is an important task concerning product quality and user experience, and by continuously optimizing product design, the market competitiveness of products and user satisfaction can be improved [6], [7].

With the development of artificial intelligence, product design optimization also ushered in the development trend of intelligence [8], [9]. Intelligent product design optimization is one of the hot areas of today's science and technology development [10]. In this context, the integration of cognitive science and machine vision technology promotes the intelligent development of product design optimization [11]. Cognitive science is a discipline that studies human cognition and thinking process, which covers the knowledge of psychology, computer science, neuroscience and other disciplines [12], [13]. And machine vision technology, as an important branch of artificial intelligence, is a technology that simulates human vision, using equipment such as computers and video cameras to enable computers to receive, process and interpret image or video data [14]-[16]. It combines several disciplines such as image processing, pattern recognition, computer vision, and artificial intelligence, and is widely used in manufacturing, healthcare, traffic monitoring, military security, and other fields [17], [18]. The integration of cognitive science and machine vision technology optimizes product design by intelligently analyzing the user's needs, product function positioning, etc., which not only helps to improve the quality of the product, but also effectively improves the user's experience, which is of great significance for the sustainable development of the product [19]-[22].

Modern product design is facing unprecedented complex challenges. Increased market competition, diversification of user needs and accelerated speed of technological updates make it difficult for traditional product design methods to cope. Product design is no longer a simple function realization or appearance beautification, but a systematic project that needs to consider multiple factors such as user experience, environmental impact, and market positioning. Especially in the field of intelligent products, how to balance the technical feasibility and user acceptance, and how to combine complex functions with simple interactions have become difficult problems for designers to solve. Cognitive science, as a discipline that studies human thinking, perception and behavior, provides a theoretical foundation for understanding the deep mechanism of user-product interaction. It reveals how humans process information, make decisions, and form aesthetic judgments, and this knowledge is of great value in predicting users' reactions to products. On the other hand, machine vision technology, as an important branch of artificial intelligence, is able to simulate the human visual system to collect, process and analyze images. This technology can not only accurately capture the morphological characteristics of products, but also quantitatively evaluate and optimize them through algorithms, providing an objective basis for product design. However, the application of cognitive science and machine vision technology in product design is often separated. Cognitive science focuses on qualitative analysis and lacks precise mathematical models; machine vision technology focuses on image processing and feature extraction, ignoring human cognitive factors. The potential of the combination of the two has not been fully explored, especially in the application of intelligent product design optimization, which needs to be studied in depth. In addition, most of the existing product design optimization methods focus on a single objective, such as cost minimization or performance maximization, and it is difficult to deal with multi-objective optimization problems. Smart product design, on the other hand, precisely requires trade-offs and optimization in multiple dimensions, such as functionality, user-friendliness, and aesthetics.

Based on the above background, this study proposes an intelligent product design optimization method that integrates cognitive science and machine vision technology. Considering user needs and aesthetic forms as complex adaptive systems, the study draws on the theory of biological evolution, adopts improved Gray coding to encode product features, and constructs a multi-objective optimization model based on the NSGA-II algorithm. By quantifying the relationship between user cognition and product features, automatic optimization and iteration of product design is realized. Meanwhile, cognitive experiments are designed to verify the effectiveness of the method and explore the impact of different types of external incentives on design innovation. The research results are expected to provide a new theoretical framework and practical tools for intelligent product design, improve design efficiency and product market competitiveness, and promote the joint improvement of product innovation and user experience.

## II. Design strategies based on cognitive science and machine vision

### *II. A. Machine vision technology*

Machine vision technology is simply the use of machines instead of the human eye to do object image measurement and judgment, machine vision system is through the machine vision products will be photographed by the target object is converted into image signals, transmitted to the special image processing system, so as to get the form of the object being photographed information, the camera through the distribution of pixels, brightness, color and other information will be converted into digital signals form of information. The camera converts the morphological information into digital signals through the distribution of pixels, brightness, color and other information. The digital signals are transmitted to the image algorithm processing equipment, and the features of the target are extracted through various mathematical operations, and various discriminations are made on the images according to these features, and finally, the results of the discriminations are used to manipulate the on-site equipment to perform further operations on the objects to be photographed. A typical industrial machine vision system mainly includes the following hardware equipment: light source, lens, camera, image processing unit, image processing software, monitor, communication input and output units. One of the light source is an important factor affecting the input of the machine vision system, due to the different light environment, can directly affect the quality of the imaging effect after the image shooting. Lens is another important factor that affects the input of machine vision system, because there are many types of lenses, and the optical ability of each lens is different, which has a great influence on the distortion of imaging. Camera is the most important hardware in the imaging system, the camera is responsible for the lens input light through the target surface chip is converted to digital signals, different target surface chip selection will also greatly affect the final effect of imaging. In general, the machine vision system is divided into two modules: the hardware part is responsible for converting the object to be photographed into digital information to be transmitted to the software part, and the software is responsible for processing the digital image information by using various types of image processing algorithms, and both of them are of indispensable importance [23].

### *II. B. Organizational form of the elements in the perspective of cognitive science*

#### II. B. 1) Organizational form of user requirements

Complex adaptive system features a kind of system that has the ability to interact and regulate with the environment, and also has complex system features, and how to specifically organize the user's needs into a system is one of the difficulties of this research. Complex adaptive systems have seven basic characteristics, and the specific user needs that exist in the social consensus are viewed as a complex adaptive system [24].

Regarding the individual of the adaptive system of user demand, the user's demand for a specific product concept is regarded as an individual in this system, in which the specific product concept and functionality used should meet the following characteristics: (1) A product category with a certain scale of general public awareness. (2) has a more obvious functional tendencies, such as backpacks need to have storage functions, flashlights need to have lighting functions, fishing rods have fishing functions. (3) The product itself and the user demand is not strong binding, for example, the fan products itself product purpose is to fan cooling, but the current society, many fans decorative significance than cooling significance, and many users are also for its decorative significance and purchase of the fan. (4) product features should be multi-functional, or functionality can be increased or reduced, the product is designed to the user's hand, is an objective existence of the physical object, with the user's use, there may be more features to be tapped, or redundant features are canceled, (5) different functions directly have a more pronounced hierarchical relationship, for example, the hard disk has a data storage function, the function of data storage capacity, data movement speed, data storage capacity, data movement speed, data movement speed, data movement speed, data movement speed, data movement speed, data movement speed, data movement speed, data movement speed and so on, and so on. For example, hard disk has data storage function, under this function, there are data storage capacity, data movement speed, data error reporting rate and other functional parameters as the user's needs in the data storage below the subdivision and derivation. (6) For individual users, the demand is often random and variable, while the group demand has a certain degree of stability, the demand has a tendency and there are primary and secondary needs. User demand as an individual in the system, will be spontaneous to the function, the intensity of development will be mainly with the cognition of the product to enhance or weaken, that is to say, if the public can't cognize the demand and the product function of the direct cause and effect relationship, then the user is the demand will not go to buy a product that can solve the function of the demand, and the function of the user's needs and changes.

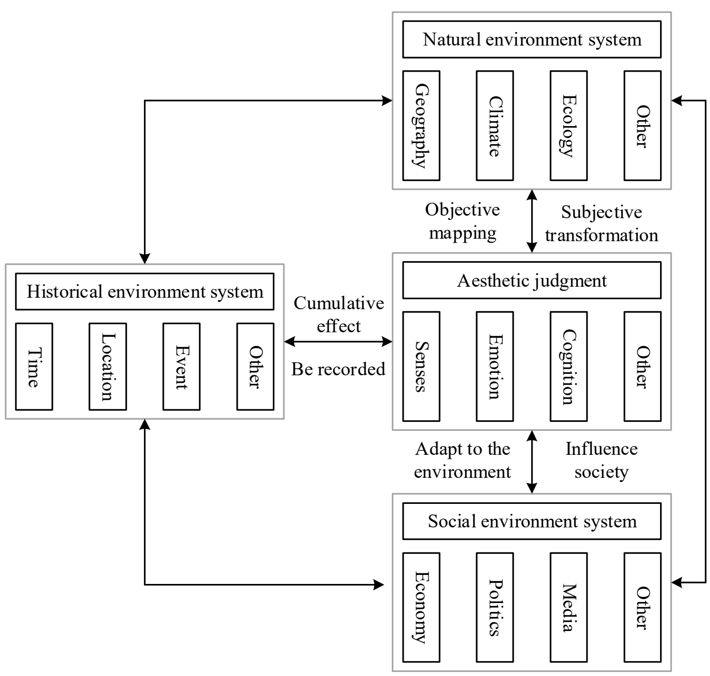


Figure 1: Aesthetic form system

#### II. B. 2) Aesthetic forms organizational patterns

And it is equally compatible to view the aesthetic tendencies of specific people existing in social consensus as a complex adaptive system. Compared to the complex adaptive system in which the user's needs are the main subject, the system scope of the user's aesthetic tendency is wider compared to the needs, but the aesthetic form is relatively independent from the specific aesthetic form that exists. The aesthetic form is not static, and will change because of the influence of the external environment on people. The aesthetic form system is shown in Figure 1, the aesthetic form can be divided into an internal system and an external system, the external system will be expressed externally and affect the external, and the external environment also affects the aesthetic form itself through the external system. The internal system determines the development direction of the aesthetic form and its scale. The characteristics of the aesthetic form are the result of the metabolism of the internal system and the external system through the interaction of energy and matter with the external environment.

### *II. C.Intelligent product design optimization model construction*

#### II. C. 1) Product optimization feature coding

When the genetic algorithm is applied to the industrial design field, the most commonly used coding method is binary coding, but the binary coding has some defects in the scatter processing, so this paper chooses the improved mode of binary coding - Gray coding, Gray coding just makes up for the defects of binary coding, and at the same time, it also has the binary coding convenient and fast advantages [25].

The binary encoding constitutes an individual genotype as a binary symbol string encoded using the binary symbol set {1, 0}. The solution accuracy of the problem being solved affects the length of the binary encoded symbol string during the encoding process. For example, suppose there is a variable $x$ whose domain of definition is $[a,b]$ and whose precision is required to be 10-5, so we need to divide $[a,b]$ into .equal-length intervals of $(b-a)\times 10^5$ portions and represent each interval as a binary string, when any binary string $\langle S_{l-1}, S_{l-2}, ..., S_0 \rangle$ is chosen to correspond to a point in the domain of definition $[a,b]$, which is the process of transforming a variable from the space of real numbers to the space of binary bit strings. The advantage of the binary coding method is that it is convenient and fast, the disadvantage is that the local search ability of the solution space is poor, and the optimization ability for continuous functions is also poor. The deformed Gray code based on binary coding can overcome the disadvantages of binary coding to some extent, but retains its advantages of convenience and speed.

Gray coding method is characterized by the two consecutive real numbers encoded in this way, the difference between their corresponding Gray codes is only one code bit, which is an optimized deformation of binary coding. The conversion formula between Gray codes and standard binary codes has the following rule: suppose there is a binary code $B = b_m b_{m-1} ... b_2 b_1$, and its corresponding Gray code is $G = g_m g_{m-1} \cdots g_2 g_1$, and the conversion formula from binary code to Gray code is:

$$g_m = b_m \quad g_i = (b_{i+1}) \oplus (b_i) \tag{1}$$

The conversion formula from Gray code to binary is:

$$b_m = g_m \quad b_i = (b_{i+1}) \oplus (g_i) \tag{2}$$

where $i = m-1, m-2...2, 1$.

The conversion between binary and Gray code is shown in Table 1.The advantage of this coding method is that it improves the local search capability of the algorithm with respect to the binary coding method. Therefore, Gray code is chosen to encode the product styling optimization features in this study.

Table 1: Binary and gray transformation

| Decimal system | Binary | Gray code |
|---|---|---|
| 0 | 0000 | 0000 |
| 1 | 0001 | 0001 |
| 2 | 0010 | 0011 |
| 3 | 0011 | 0010 |
| 4 | 0100 | 0110 |
| 5 | 0101 | 0111 |
| 6 | 0110 | 0101 |
| 7 | 0111 | 0100 |
| 8 | 1000 | 0100 |
| 9 | 1001 | 0101 |
| 10 | 1010 | 1111 |

### II. C. 2) Product optimization process based on NSGA-II algorithm

The product styling optimization process based on NSGA-II algorithm includes three key steps:

(1) Design of fitness function of product features

A single product styling design scheme is a separate individual in the genetic algorithm, the fitness of a single individual is a measure that expresses the degree of survival advantage of the individual in the contemporary population, which can be used to assess the individual's good or bad in the process of genetic manipulation, and the corresponding product is the product's good or bad response in the market. The fitness is derived by performing calculations through the fitness function, which is also known as the evaluation function, and the individual fitness is mainly assessed by the goodness of the individual evaluation [26].

The above step describes the type of product styling design optimization problem, according to the corresponding objective function of the problem to find its individual fitness function. The expression of the fitness function is as follows:

$$F_i = \sum_{m=1}^{m} \lambda_m f_m \tag{3}$$

where $m = 1, 2, ..., m-1, m$ , $\lambda_m$ is the weighted value of the importance of the modeling features, and $f_m$ is the relationship function between the user satisfaction of the modeling features and the eigenvalues, i.e., the objective function.

(2) Non-dominated ordering and crowding calculation

From the second generation of product modeling population onwards, each generation of the parent population into the offspring population, to generate a new generation of product modeling population, these product modeling population contains two generations of the population of the more excellent product modeling design solutions, and then through the non-dominated sorting of these product modeling of all the individuals and congestion calculation, with these two parameters as the selection conditions for selecting new product modeling solutions to generate a new product modeling population, the new product modeling program. The new product modeling population is then generated by selecting new product modeling solutions by using these two parameters as selection conditions.

Crowding degree refers to the density of individuals around the specified individual in the population, through the calculation and comparison of crowding degree $n_d$ , so that the obtained product modeling individuals are more evenly distributed in the target space, the calculation process is as follows: so that the parameter $n_d = 0, n \in 1, ..., N$ , for each objective function $f_m$ , based on the objective function, the same level of the individuals in ascending order of the sequence, noting that $f_m^{\max}$ is the maximum value of the individual objective function $f_m$ , noting that $f_m^{\min}$ is the minimum value of the individual objective function $f_m$ , for the congestion degree $1_d = N_d = \infty$ at the edge of the sorted sequence, calculate:

$$n_d = n_d + \frac{(f_m(i+1) - f_m(i-1))}{(f_m^{\max} - f_m^{\min})} \tag{4}$$

where $f_m(i+1)$ is the value of the objective function of the individual one place after sorting.

(3) Genetic parameter setting and elite strategy selection

Because NSGA-II algorithm is based on the first generation of NSGA algorithm added elite strategy in the selection operation, to ensure the retention of the Pareto optimal solution by placing all the good individuals in the parent population into the offspring population, the specific operation is to directly merge the parent and the offspring together and then carry out the nondominated sorting. This step is to select n individuals by elite strategy selection to form the next generation population $p_{t+1}$ . The above genetic operation is repeated until the termination condition is reached in the offspring, or other set termination conditions are met, the genetic operation is stopped and the population optimization result is obtained.

### II. C. 3) Reverse decoding optimized design solution

After product styling optimization through the product styling optimization model based on NSGA-II algorithm, the optimization result is the genetic composition of the design scheme, the gene is composed of the combination of encoded data, but this kind of data to the optimized product styling design scheme still needs the process of reverse decoding. Analogous to the gene expression in biological genetics, the gene determines the expression of traits, it is through reverse compilation to produce proteins, etc., and ultimately expressed as a biological expression of different traits, corresponding to the gene expression of the product styling, the product styling is the biological expression of traits. Therefore, in addition to the need for the reverse decoding of the product characteristics of the gene for the optimization of design information, but also need to be based on the decoded product optimization design information, styling optimization design scheme presentation, intuitive expression of the results of the product styling optimization.

## III. Experimental design and analysis of results

### *III. A. Experimental design*

The purpose of this study is to establish the correlation between designers' focus on incentives and the generation of creative solutions, and to summarize the law of the influence of different incentives on the generation of creative solutions and designers' thinking activities from a quantitative perspective. Thus, it provides guidance for the application of incentive information in design practice, and guides designers to select incentives purposefully in the process of innovative design, enhances their creativity, and promotes the generation of innovative design solutions. For this experimental purpose, this study designed cognitive experiments and invited 30 designers with the same experiential background as participants in an out-of-voice thinking experiment. The participants were graduate students (average age 26) from the Key Laboratory of Innovative Design and Innovation Methods, who had some theoretical research and practical experience in innovative design.

#### III. A. 1) Product design experiment

This experiment requires the designer to think out loud and provides the designer with three types of external incentives: far-domain incentives, constraints, and near-domain incentives Three types of external incentives are provided to the designers, and the experimental process for each group consists of three parts: a pre-experiment, a formal experiment, and a retrospective interview. Therefore, this experiment will provide experimental participants with three types of external incentive materials: domain incentives (S1), constraints (S2) and near-domain incentives (S3). The near-domain incentives are example products or conceptual products belonging to the same category as the design task; the far-domain incentives are unrelated things or phenomena belonging to a different domain from the design task; and the constraints are added design requirements that need to be fulfilled.

Table 2: Object-oriented design coding scheme for product innovation

<table>
<tr><th>Cognitive activity</th><th>Activity description</th><th>Specific classification of cognitive activities</th></tr>
<tr><td rowspan="4">Physical behavior</td><td rowspan="4">The drawing and sketch of the concept sketch draws directly related behaviors</td><td>D-sketch drawing</td></tr>
<tr><td>L-review the previous sketch</td></tr>
<tr><td>Ls-view design incentives/constraints and other behaviors of the current sketch</td></tr>
<tr><td>M-other behaviors</td></tr>
<tr><td rowspan="5">Perceptual layer behavior P</td><td rowspan="5">The description of the concept sketch describes the spatial visual characteristics (structural characteristics) of the conceptual sketch, such as structural form, material, spatial relationship, etc</td><td>PF-drawing a new sketch structure</td></tr>
<tr><td>PO-describe existing sketch structures</td></tr>
<tr><td>PM-establish the connection of different sketch structures</td></tr>
<tr><td>PS-analysis design incentives or existing sketches, or other visual features</td></tr>
<tr><td>PA-analysis design incentives or structural relationships between elements in the existing sketch</td></tr>
<tr><td rowspan="3">Functional F</td><td rowspan="3">The non-visual characteristics associated with functional or abstract concepts in the description of the product function</td><td>FN-sketch produces new features</td></tr>
<tr><td>FA-analysis design incentives or existing sketches</td></tr>
<tr><td>FC-analysis of the interaction between design incentives or existing sketches</td></tr>
<tr><td rowspan="3">Conceptual behavior</td><td rowspan="3">Other, not by physical or spatial vision, characterized by direct representation of cognitive behavior</td><td>E-bias and aesthetic evaluation</td></tr>
<tr><td>K-collect information and knowledge retrieval</td></tr>
<tr><td>G-set goals/design ideas</td></tr>
</table>

#### III. A. 2) Spoken transcription and coding scheme creation

After the completion of the experiment, the experimenters were required to convert the recorded spoken data into a transcript report, and to segment and code the transcript report. Since the design content-oriented coding scheme can reflect the visual and non-visual information processing in human cognitive processes, i.e., what they see, notice, think about, and retrieve from their memories, this study used this scheme to code the design behaviors of the experimental participants. The focus of this coding was on the designer's sketching, observational behavior, sketch revision, and the designer's discussion of structural, functional, and evaluative decisions about the designed product. Based on the content-oriented coding scheme, this study adapted the specific categorization of cognitive activities to the cognitive behaviors focused on in the actual cognitive experiments, and the results are shown in Table 2.

#### III. A. 3) Link diagram creation

Based on the segmentation and coding results of each experimental participant's spoken data, the corresponding link diagrams were created. Design steps were numbered according to the order of the spoken data produced by the experimental participants, and links between the corresponding design steps were indicated when one or more of the following criteria were met.

(1) Experimental participants directly referenced previous design ideas.

(2) The presence of obvious gestures, sketches, or words related to previous design ideas.

(3) Functional, structural, or behavioral similarities exist between design ideas.

(4) Design steps occurred sequentially in the same idea.

All processed experimental data were statistically analyzed by IBM's Statistical Package for the Social Sciences SPSS software.

### *III. B. Experimental results and analysis*

#### III. B. 1) Analysis of intelligent product design optimization solutions

In order to analyze the impact of different cognitive incentives and constraints on the results of product design, we counted the number of solutions generated by the three groups of experimental participants in the free design phase as shown in Table 3.

Table 3: The number of sketches was produced by the free design stage

| Far field incentive group | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Participant | F1 | F2 | F3 | F4 | F5 | F6 | F7 | F8 | F9 |
| Rough draft | 4 | 7 | 3 | 6 | 5 | 6 | 4 | 5 | 4 |
| Participant | F10 | F11 | F12 | F13 | F14 | F15 | F16 | F17 | F18 |
| Rough draft | 5 | 4 | 7 | 6 | 8 | 7 | 5 | 6 | 5 |
| Mean=4.28±1.70 | | | | | | | | | |
| Close domain incentive group | | | | | | | | | |
| Participant | I1 | I2 | I3 | I4 | I5 | I6 | I7 | I8 | I9 |
| Rough draft | 4 | 4 | 1 | 5 | 4 | 7 | 4 | 4 | 4 |
| Participant | I10 | I11 | I12 | I13 | I14 | I15 | I16 | I17 | I18 |
| Rough draft | 5 | 4 | 5 | 2 | 2 | 4 | 5 | 5 | 4 |
| Mean=3.11±1.29 | | | | | | | | | |
| Constraint group | | | | | | | | | |
| Participant | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 |
| Rough draft | 3 | 6 | 10 | 3 | 5 | 3 | 4 | 3 | 6 |
| Participant | C10 | C11 | C12 | C13 | C14 | C15 | C16 | C17 | C18 |
| Rough draft | 6 | 7 | 6 | 4 | 5 | 8 | 6 | 6 | 7 |
| Mean=4.22±2.10 | | | | | | | | | |

The number of programs generated in each of the design stimulation phases is shown in Table 4.

In the free design phase, the means of the number of scenarios generated by participants in the far-field stimulus, near-field stimulus, and constraint groups (18 participants in each group) were 4.28 ± 1.70, 3.11 ± 1.29, and 4.22 ± 2.10, respectively.In the design stimulus phase, the means of the number of scenarios generated by participants in these three experimental groups were 3.61 ± 1.73, 2.5 ± 1.52, and 2.44±1.47.

Table 4: The participants produced the number of sketches

| Far field incentive group | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Participant | F1 | F2 | F3 | F4 | F5 | F6 | F7 | F8 | F9 |
| Rough draft | 3 | 3 | 2 | 1 | 2 | 6 | 8 | 3 | 3 |
| Participant | F10 | F11 | F12 | F13 | F14 | F15 | F16 | F17 | F18 |
| Rough draft | 7 | 5 | 6 | 4 | 5 | 7 | 6 | 7 | 5 |
| Mean=3.61±1.73 | | | | | | | | | |
| Close domain incentive group | | | | | | | | | |
| Participant | I1 | I2 | I3 | I4 | I5 | I6 | I7 | I8 | I9 |
| Rough draft | 5 | 4 | 4 | 2 | 4 | 3 | 1 | 5 | 4 |
| Participant | I10 | I11 | I12 | I13 | I14 | I15 | I16 | I17 | I18 |
| Rough draft | 3 | 4 | 2 | 3 | 4 | 1 | 5 | 3 | 4 |
| Mean=2.5±1.52 | | | | | | | | | |
| Constraint group | | | | | | | | | |
| Participant | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 | C9 |
| Rough draft | 1 | 2 | 4 | 5 | 7 | 5 | 4 | 1 | 2 |
| Participant | C10 | C11 | C12 | C13 | C14 | C15 | C16 | C17 | C18 |
| Rough draft | 2 | 4 | 3 | 1 | 1 | 2 | 3 | 2 | 4 |
| Mean=2.44±1.47 | | | | | | | | | |

First, we conducted a between-group ANOVA on the number of solutions generated by the three groups of experimental participants in the design stimulus phase, and the results showed that the between-group significance of the number of solutions generated by the three groups of experimental participants in the design stimulus phase was $p>0.05$ ($p=0.075$, $F=2.812$), which indicated that there was no significant difference in the effect of the incentives and constraints of the distant and near domains on the number of solutions generated in the design stimulus phase. . The homogeneity of the ANOVA was tested by Levene's Test (Levene's Test), which resulted in a significance $p=0.946>0.05$, indicating that the ANOVA results were reliable. Second, we compared the differences in the number of scenarios generated by the three groups of experimental participants during the free design phase versus the design stimulus phase of their respective experiments. The results showed that the mean values of the number of scenarios generated by the three groups of experimental participants during the design stimulus phase were reduced compared to the free design phase, as influenced by the stimulus materials. In particular, participants in the far and near domain stimulus groups did not differ significantly in the number of schema sketches produced in the pre- and post-stimulus phases before and after being provided with the cognitive stimulus ($p$ far domain = 0.643 > 0.05, $F$ far domain = 0.230. $p$ near domain = 0.148 > 0.05, $p$ near domain = 2.267). In contrast, participants in the constraints group generated significantly fewer solutions in the design stimulus phase compared to the free design phase ($p$ constraints=0.024<0.05, $F$ constraints=5.847), which may be due to the constraints acting as a constraint on the experimental participants, limiting them from exploring more solutions, which led to a decrease in the number of solutions generated.

**III. B. 2) Analysis of programmatic advancement**

First, from the demonstration case itself, the technical attributes identified based on the functional requirements of the intelligent floor sweeping robot are the main inputs for subsequent fuzzy delineation. Customer requirements are mapped to the technical attributes in the fuzzy environment, and the importance of the technical attributes is evaluated, so that a customer-oriented intelligent floor sweeping robot is designed to improve customer satisfaction. Technical conflicts are identified by judging the relationship between technical attributes, and the improved TRIZ theory is used to resolve these conflicts, which reduces the risk of failure of the conceptual design of intelligent floor sweeping robots. Second, in terms of the key technologies in this chapter, the hierarchical taxonomy establishes the relationship between functional requirements and technical attributes, which not only refines the functional requirements, but also simplifies the set of technical attributes and clearly expresses the hierarchical relationship of technical attributes. Intelligent product optimization based on NSGA-II algorithm efficiently handles the information in the transformation process and evaluates the importance of technical attributes from the perspective of multi-criteria decision making, which improves the accuracy of the transformation of customer requirements to technical attributes. The technical attributes and importance ranking are shown in Table 5. The resolution of the closeness coefficient of intelligent product optimization based on NSGA-II algorithm is higher. In addition, the linear fitting method identifies the technical conflicts and then resolves the technical conflicts, which enhances the usability of technical attributes.

Table 5: Technical properties and importance sort

| Technical properties | $d_i^+$ | $d_i^-$ | Coefficient of proximity |
|---|---|---|---|
| TA1 | 0.3878 | 0.5214 | 0.5897 |
| TA2 | 0.3602 | 0.6687 | 0.6473 |
| TA3 | 0.5022 | 04546 | 0.4882 |
| TA4 | 0.6625 | 0.2663 | 0.2809 |
| TA5 | 0.6257 | 0.3415 | 0.3528 |
| TA6 | 0.2911 | 0.9547 | 0.3532 |
| TA7 | 0.2694 | 0.0496 | 0.1557 |
| TA8 | 0.8774 | 0.0001 | 0.0001 |
| TA9 | 0.6663 | 0.2024 | 0.2358 |
| TA10 | 0.4685 | 0.4099 | 0.4678 |
| TA11 | 0.6799 | 0.2805 | 0.2887 |
| TA12 | 0.6149 | 0.2485 | 0.3024 |
| TA13 | 0.1845 | 0.0745 | 0.3025 |
| TA14 | 0.1784 | 0.0001 | 0.0001 |

The function of Cp versus Ct is shown in Fig. 2. Finally, in terms of potential industrial benefits, integrating customer requirements into the conceptual design of smart products, customers prefer to use such products, which improves customer loyalty to smart products. Smart product optimization based on NSGA-II algorithm realizes the transformation of customer requirements to technical attributes to design customer-oriented smart products. The conflict between technical attributes is resolved to make the designed smart products more reasonable and feasible.

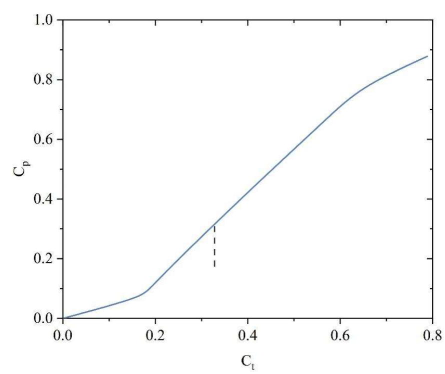


Figure 2: Function of Cp and Ct

## IV. Conclusion

The intelligent product design optimization method integrating cognitive science and machine vision technology shows significant advantages in experimental validation. By constructing user requirements and aesthetic forms as a complex adaptive system and optimizing them with Gray coding and NSGA-II algorithm, the accurate generation of multi-objective design solutions is achieved. The experimental data show that far-field stimulation has a positive impact on design solution generation, with the number of solutions in the stimulation phase averaging 3.61±1.73, which is higher than that of the near-field stimulation group (2.5±1.52) and the constraints group (2.44±1.47).The results of the evaluation of the technological attributes show that the coefficient of the closeness of the TA2 reaches 0.6473, while that of the TA8 and the TA14 is only 0.0001, which suggests that the significant differences in the contribution of technical attributes to user satisfaction. Based on these findings, a design strategy combining external cognitive incentives and optimization algorithms can be established to focus on optimizing specific technical attributes. This method enables smart product design to shift from subjective experience to data-driven, solves the conflict problem between technical attributes, and improves product usability and market competitiveness. Future research can further explore the combination effect of different incentive types, improve the encoding and decoding mechanism of product features, and expand the scope of application areas. This fusion approach provides new ideas for the innovative design of intelligent products and promotes the interdisciplinary integration of design science and engineering technology.

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