兰州理工大学博士研究生科研情况一览表

学院：机电工程学院　　姓名：邱 凯　　学号：191080203003　　2023 年 5 月 10 日

发 表 学 术 论 文 情 况				
发表日期	论 文 题 目	刊物名称/刊号	本人排名	刊物级别
2020	Evaluation and Balance of Cognitive Friction: Evaluation of Product Target Image Form Combining Entropy and Game Theory	Symmetry-Basel	1/4	SCI
2022	Research on product target image cognition based on complex network theory and game theory	Journal of Advanced Mechanical Design, Systems, and Manufacturing	1/4	SCI
2022	面向多域协同的复杂产品再设计模块主从识别	浙江大学学报(工学版)	1/5	EI（网络版）
合计：3 篇　本人签名：邱凯　导师签名：[签名]　主管院长签名：[签名]				

注：1、仅列出本人第一或者导师第一、本人第二的学术论文和科研成果。

2、刊物级别分为：SCI、SSCI、A&HCI、EI（注明光盘版或网络版）、CPCIE、CSCD（注明核心版或扩展版）、CSSCI、中文核心期刊、普通 CN 刊物。

3、奖励级别分为：国家级、省部级、厅局和省级及以上学会级、校级（需写明获奖的具体等级，如省部级三等奖）。

4、专利分为：发明专利、实用新型专利和外观设计专利。

5、双面打印，仅限一页。

6、一式 25 份，一份原件，其他可复印。

（此报告为预览模式，仅供核对报告数据）

图书馆

文献检索报告
SCI-E 收录

兰州理工大学图书馆 LUTLIB

报告编号：R2023-0280 SCI-E 收录

数据库：科学引文索引 (Science Citation Index Expanded) 时间范围：1900年至2023年	委托人：邱凯 委托单位：兰州理工大学 机电工程学院	检索人员：__________ 检索日期：2023年5月30日

检索结果：被 SCI-EXPANDED 收录文献 2 篇
筛选结果： 被 SCI-EXPANDED 收录文献 2 篇

#	作者	标题	来源出版物	出版物类型	入藏号
1	**Qiu, K**; Su, JN; Zhang, XX; Yang, WJ	Evaluation and Balance of Cognitive Friction: Evaluation of Product Target Image Form Combining Entropy and Game Theory	***SYMMETRY-BASEL*** 2020, 12 (9): 1398.	J Article	WOS:000587594200001
2	**Qiu, K**; Su, JN; Zhang, ST; Yang, WJ	Research on product target image cognition based on complex network theory and game theory	***JOURNAL OF ADVANCED MECHANICAL DESIGN SYSTEMS AND MANUFACTURING*** 2022, 16 (6): 17.	J Article	WOS:000885527400001
				合计	2

收录文献附录

第 1 条，共 2 条:
标题: Evaluation and Balance of Cognitive Friction: Evaluation of Product Target Image Form Combining Entropy and Game Theory
作者: Qiu, K (Qiu, Kai); Su, JN (Su, Jianning); Zhang, XX (Zhang, Xinxin); Yang, WJ (Yang, Wenjin)
来源出版物: SYMMETRY-BASEL **卷:** 12 **期:** 9 **文献号:** 1398 **出版年:** SEP 2020
入藏号: WOS:000587594200001
文献类型: Article **出版物类型:** J
作者地址: [Qiu, Kai; Su, Jianning; Yang, Wenjin] Lanzhou Univ Technol, Sch Mech & Elect Engn, Lanzhou 730050, Peoples R China.; [Su, Jianning] Lanzhou Univ Technol, Sch Design Art, Lanzhou 730050, Peoples R China.; [Zhang, Xinxin] Hebei Univ Technol, Sch Architecture & Art Design, Tianjin 300401, Peoples R China.; Hebei University of Technology
通讯作者地址: Su, JN (通讯作者)，Lanzhou Univ Technol, Sch Mech & Elect Engn, Lanzhou 730050, Peoples R China.; Su, JN (通讯作者)，Lanzhou Univ Technol, Sch Design Art, Lanzhou 730050, Peoples R China.

第 2 条，共 2 条:
标题: Research on product target image cognition based on complex network theory and game theory
作者: Qiu, K (Qiu, Kai); Su, JN (Su, Jianning); Zhang, ST (Zhang, Shutao); Yang, WJ (Yang, Wenjin)
来源出版物: JOURNAL OF ADVANCED MECHANICAL DESIGN SYSTEMS AND MANUFACTURING **卷:** 16 **期:** 6 **出版年:** 2022
入藏号: WOS:000885527400001
文献类型: Article **出版物类型:** J
作者地址: [Qiu, Kai; Yang, Wenjin] Lanzhou Univ Technol, Sch Mech & Elect Engn, 36 Pengjiaping Rd, Lanzhou 730050, Peoples R China.; [Su, Jianning; Zhang, Shutao] Lanzhou Univ Technol, Sch Design Art, 287 Langongping Rd, Lanzhou 730050, Peoples R China.
通讯作者地址: Su, JN (通讯作者)，Lanzhou Univ Technol, Sch Design Art, 287 Langongping Rd, Lanzhou 730050, Peoples R China.

（此报告为预览模式，仅供核对报告数据）

图书馆

文献检索报告
EI 收录

兰州理工大学图书馆 LUTLIB

报告编号：R2023-0280 EI 收录

数据库：工程索引 (Engineering Index) 时间范围：1884年至2023年	委托人：邱凯 委托单位：兰州理工大学 机电工程学院	检索人员：__________ 检索日期：2023年5月30日

检索结果：被 EI-Compendex 收录文献 2 篇
筛选结果： 被 EI-Compendex 收录文献 2 篇

#	作者	标题	来源出版物	出版物类型	入藏号
1	**Qiu, Kai**; Su, Jianning; Zhang, Shutao; Yang, Wenjin	Research on product target image cognition based on complex network theory and game theory	***Journal of Advanced Mechanical Design, Systems and Manufacturing*** 2022, 16 (6): 21-00155.	Journal article (JA)	20225113279254
2	**Qiu, Kai**; Su, Jian-Ning; Zhang, Shu-Tao; Zhang, Zhi-Peng; Liu, Shi-Feng	Leader-follower identification of complex product redesign modules for multi-domain collaboration 面向多域协同的复杂产品再设计模块主从识别	***Zhejiang Daxue Xuebao (Gongxue Ban)/Journal of Zhejiang University (Engineering Science)*** 2022, 56 (12): 2358-2366+2391.	Journal article (JA)	20230213379169
				合计	2

收录文献附录

第 1 条，共 2 条:
Accession number:20225113279254
Title:Research on product target image cognition based on complex network theory and game theory
Authors:Qiu, Kai (1); Su, Jianning (2); Zhang, Shutao (2); Yang, Wenjin (1)
Author affiliation:(1) School of Mechanical & Electronical Engineering, Lanzhou University of Technology, 36 Pengjiaping Road, Lanzhou; 730050, China; (2) School of Design Art, Lanzhou University of Technology, 287 Langongping Road, Lanzhou; 730050, China
Corresponding authors:Qiu, Kai; Yang, Wenjin
Source title:Journal of Advanced Mechanical Design, Systems and Manufacturing Volume:16; Issue:6; Issue date:2022; Publication year:2022; Article number:21-00155; Language:English; E-ISSN:18813054;
Document type:Journal article (JA)
Database:Compendex
Compilation and indexing terms, Copyright 2023 Elsevier Inc.

第 2 条，共 2 条:
Accession number:20230213379169
Title:Leader-follower identification of complex product redesign modules for multi-domain collaboration
Authors:Qiu, Kai (1); Su, Jian-Ning (2); Zhang, Shu-Tao (2); Zhang, Zhi-Peng (1); Liu, Shi-Feng (1)
Author affiliation:(1) School of Mechanical and Electronical Engineering, Lanzhou University of Technology, Lanzhou; 730050, China; (2) School of Design Art, Lanzhou University of Technology, Lanzhou; 730050, China
Corresponding author:Su, Jian-Ning(sujn@lut.edu.cn)
Source title:Zhejiang Daxue Xuebao (Gongxue Ban)/Journal of Zhejiang University (Engineering Science) Volume:56; Issue:12; Issue date:December 2022; Publication year:2022; Pages:2358-2366+2391; Language:Chinese; ISSN:1008973X; CODEN:CHHPDK;
Document type:Journal article (JA)
Database:Compendex
Compilation and indexing terms, Copyright 2023 Elsevier Inc.

symmetry

MDPI

Article

Evaluation and Balance of Cognitive Friction: Evaluation of Product Target Image Form Combining Entropy and Game Theory

Kai Qiu [1], **Jianning Su** [1,2,*], **Xinxin Zhang** [3] **and Wenjin Yang** [1]

1 School of Mechanical & Electronical Engineering, Lanzhou University of Technology, Lanzhou 730050, China; 191080203003@lut.edu.cn (K.Q.); 171080203016@lut.edu.cn (W.Y.)
2 School of Design Art, Lanzhou University of Technology, Lanzhou 730050, China
3 School of Architecture and Art Design, Hebei University of Technology, Tianjin 300401, China; y10160052@mail.ecust.edu.cn
* Correspondence: sujn@lut.cn

Received: 28 July 2020; Accepted: 20 August 2020; Published: 21 August 2020

check for updates

Abstract: With the great progress of product development technology, product forms have been greatly enriched by cognitive differences; users and designers have formed a "cognitive friction" phenomenon in the product evaluation process, which results in designers being unable to grasp user emotions accurately and risks of product development failure. This paper aims to balance the cognitive differences between cognitive subjects (users and designers) and evaluates the product image form. First, image entropy is used to evaluate and extract the weight of the product target image. Second, fuzzy Theil entropy is used to evaluate the cognitive friction between cognitive subjects, and its existence and size are visually presented. Then, a cognitive friction balance model is built by combining game theory, the comprehensive evaluation weight between cognitive subjects is obtained, and the product image form is ranked and optimized. Finally, all the research steps are described in the form of a household hair dryer. The results show that fuzzy Theil entropy and game theory have significant advantages in the evaluation and balance of cognitive friction in product design. Thus, the cognitive friction evaluation and balance model constructed from the fuzzy Theil entropy and game theory do not only enable different cognitive subjects to achieve cognitive symmetry, but also screen out product forms that meet the cognitive needs of users. This finding provides the theoretical basis and practical significance for the establishment of a closed-loop model in cognitive friction balance and the reduction of cognitive differences between cognitive subjects in the entire process of product design. It also introduces new ways of thinking and methods for cognitive science research.

Keywords: cognitive friction; product image form; fuzzy Theil entropy; game theory; cognitive symmetry

1. Introduction

With the great advancement of product development technology, designers and engineers have faced difficulty achieving differentiation in implementing the functional characteristics of products. It is becoming increasingly important to design products that meet user needs and emotional experiences [1,2]. With the advancement of technology and interdisciplinary development, artificial intelligence (AI) technology has begun to play an important role in the field of product design. With innovative algorithms and powerful computing capabilities, a large number of design solutions can be generated by computers in a short time, but the reasoning for the user's emotion is still in the exploration stage [3,4]. Most of the extant studies use machine learning technology to learn the actual physiological change data to realize the prediction of emotional preference [5,6]; however, there is also a large deviation in accurately grasping the distance of emotional preference [7]. Because there is widespread user cognitive information dissipation in the actual evaluation process, users cannot accurately find the solutions they need among a large number of similar solutions after computer screening; thus, the efficiency and quality of product development is seriously affected. However, most designers produce products by using design tools to carry out conceptual plans. They not only focus on a certain stage of the design activity, but also consider the systemic nature of the entire process [8]. Emotion is injected into the entire process of product design, so that the product can be satisfied from the functional level to the user's emotional level [9], and a solution that meets the user's emotional needs can be selected for optimal design and output, which makes it particularly important to accurately grasp the emotional needs of users. Due to the differences in the mental models and professional backgrounds of users and designers, users are significantly different from designers in terms of their understanding, perception, and expression of perceptible product features, which leads to an asymmetry of cognitive information in the process of expressing needs and evaluating products.

In view of the asymmetry of cognitive information, Alan Cooper et al. proposed the concept of cognitive friction (CF) [10] and applied it to the field of product design, to express that the products developed by designers could not fully meet user expectations. This phenomenon might cause confusion for users when using the product [11]. From Alan Cooper, we know that the concept of CF involves three parts: the designer, product, and user. Among them, the product is a cognitive object, and the user and designer are cognitive subjects. In the final analysis, the generation of CF is caused by the cognitive difference between designers and users. Therefore, visually displaying and balancing CF is an important way in which to solve the cognitive difference between designers and users, which will also provide a certain theoretical basis for AI to accurately grasp users' emotions.

In current researches, in order to reduce the CF between the designer and the user and establish the correspondence between the cognitive subject's emotions and design features, complex psychological methods and models have been used by researchers. However, the existence of CF and the methods to reduce its influence were only discussed at the perceptual level, the CF was not evaluated quantitatively, and the mechanism of its generation was not discussed. All of these researches, as a result, did not solve the CF fundamentally. Product design and development still have the risk of failure due to the CF between cognitive subjects. Therefore, the quantitative evaluation and balance of CF between cognitive subjects is one of the key factors to determine the success of product development. The paper focuses on how to accurately evaluate and balance the CF between cognitive subjects to achieve the purpose of solving cognitive asymmetry. Because Kansei engineering (KE) has developed various methods for the correlation analysis of product design elements and the emotions of cognitive subjects to identify the relationship between emotional cognition and product design [12], the evaluation of CF is performed via KE and entropy theory. The evaluation of a household hair dryer is taken as an example to complete the research. First, through the collection of product sample cases and the selection of corresponding emotional vocabulary, the evaluation construction of cognitive subjects is completed. Then, based on image entropy and fuzzy Theil entropy, a CF evaluation model is established to explore the existence and size of CF by using a combination of qualitative and quantitative methods. Finally, the CF balance model, combined with game theory, is constructed to complete the optimization of the product image form based on cognitive balance.

We organize the rest of the paper as follows. Section 2 presents the related research (including perceptual engineering, image entropy and fuzzy Theil entropy, and game theory). Section 3 introduces the construction of the CF evaluation model and balance model. Section 4 conducts case studies and presents and verifies the results. Section 5 discusses the entire process, results, and significance of this paper. Finally, Section 6 provides the conclusions of this paper and recommendations for future work.

2. Related Studies

2.1. Kansei Engineering

KE [13,14] was proposed by Mitsuo Nagamachi in 1970 and is a technology that associates users' psychological perception with product design elements [15,16]. Designers can obtain the user's perceived image quickly to complete the product design that meets the user's emotional needs through KE methods [17–19]. The general process, as shown in Figure 1, is mainly divided into three steps: image acquisition, model building, and form optimization design. First, to achieve the purpose of image acquisition, a product case set and an image vocabulary set are established by collecting product samples and describing perceptual vocabulary to evaluate the product form, color, material, etc., and to obtain the user's perception [20–22]. Commonly used methods include the semantic difference (SD) method [23], physiological signal experiment method [24], natural language processing [25], and factor analysis [26]. Then, to establish the correlation between perceptual evaluation and design elements, common methods include quantitative theory I [27], rough set theory [28], optimal ideal solution ranking [29], and support vector machines [30]. Finally, researchers use intelligent algorithms to train and optimize models to guide subsequent design. These methods include deep learning [31], swarm intelligence algorithms [32], genetic algorithms [33], and a combination of multiple optimization methods [34,35].

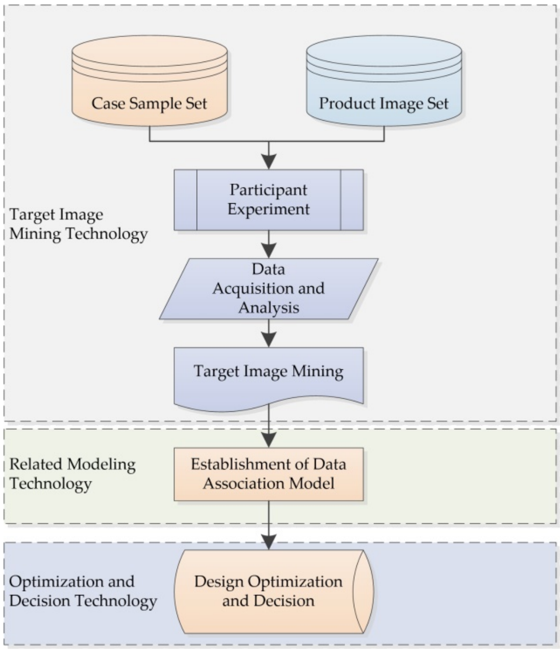

Figure 1. General flow of KE research.

Therefore, the KE method is used to collect case samples and image vocabulary to form an initial sample set and an initial image set in this paper. Then, the target sample set is established through the similarity evaluation, and the target image is evaluated by combining the SD method and the image entropy algorithm.

2.2. Cognitive Friction

Friction, as a definition in physics, emphasizes that there is a mutual obstruction between relative motion or two objects that have a tendency toward relative motion. CF is due to the resistance caused by the "grey box" or "black box" of the product to users. CF exists in many aspects. As shown in Figure 2, this resistance arises from the cognitive asymmetry between the user and designer in product design, which causes the user's cognitive discontinuity in the process of using or evaluating the product [36]. Donald Norman proposed three models of CF [37], namely the design model, user model, and system representation. He also believed that CF would be derived from these three models and the differences between them. Among them, the design model mainly expresses the designer's design concept and represents the designer's cognitive space. The user model is the concept that the product should exist in the user's psychology, including the user's experience and expectations of the product itself, and represents the user's cognitive space. The system representation is the intuitive perception that the product brings to the user and represents the product system itself.

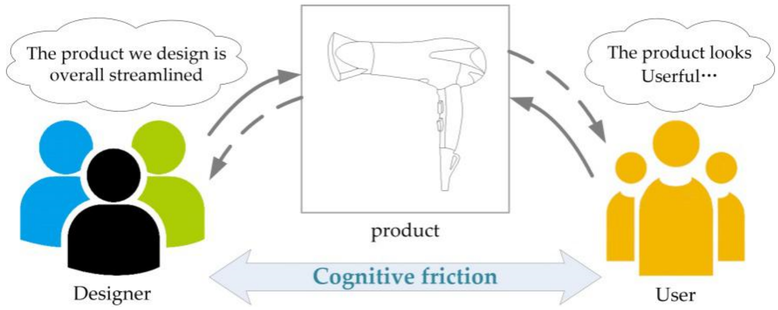

Figure 2. Schematic diagram of cognitive friction (CF) generation.

The design and use of the product are the processes of encoding and decoding. Only by understanding the user's psychological needs can the encoding process be more in line with the user's decoding habits [38]. By making the cognition symmetry, the user's cognitive resistance during the use of the product is reduced to design products that exceed user expectations. Therefore, the effective evaluation and balance of CF is a key step in improving product design. This paper establishes the CF evaluation model and balance model between the user and designer. The CF size can be intuitively reflected through the evaluation of the morphological image of the research case and amended through the CF balance model, to filter out the product form that meets the cognition of users and designers. In this way, the cognitive difference between the designer and user can be reduced, and the designer's design efficiency, while meeting the user's psychological needs, can be improved.

2.3. Game Theory

Game theory, a method derived from modern mathematics, is used to study decision-making when the behavior of the decision-making subject directly interacts, and the equilibrium problem of such decision-making [39], which is an important method of multi-attribute decision-making. The decision-making subject will consider the other party's decision in his/her own decision-making, choose the strategy that is most beneficial to him/her, and maximize his/her own profits or ultimately win; this strategy is widely used in various fields of life [40]. For example, in product form design, determining the evaluation index weights among cognitive subjects (users, designers, engineers, etc.) is also a key issue in multi-attribute decision-making. Accurate index weights are the basis for obtaining reliability evaluation results. Index weighting methods mainly include three types: the subjective weighting method, objective weighting method, and combined weighting method. The subjective weighting method relies on the experience or knowledge of the cognitive subject and is a subjectively meaningful decision, such as the analytic hierarchy process (AHP) [41]. The objective weighting method relies on the information itself to obtain weight data through calculation, such as the entropy weight method [42–44]. The combined weighting method combines subjective and objective information to determine the weight. In the study of evaluation problems, only a single subjective or objective weighting method cannot accurately express the relationship between the evaluation subjects and the true situation of the evaluated information, which is likely to lead to a lack of information and affect the evaluation results [40]. Based on game theory, the problem of information loss caused by a single weighting can be reduced to a large extent, and accurate evaluation results can be obtained through the combined weighting of the evaluation process of cognitive subjects [29].

The process of product design is a process of cognitive information games. As shown in Figure 3, we call it the "cognitive game". The product is the game object, and designers, users, engineers, etc. are the main game subjects. Only two types of cognitive subjects, users and designers, are considered in this paper. Based on users, they hope that the products can fully meet their expectations or emotional needs on the basis of satisfying the functions of the products, and designers believe that the products not only need to meet the needs of users, but should also highlight the design concept and be able to provide users with more than the expected experience effects. However, in the actual design process, due to the ambiguity of the user's perceived information, it will rely more on the designer's subjective image. In the process of product form evaluation, the strongest image of the same product is different between the user and designer, resulting in a gap in image perception between them, so the product designed by the designer cannot be fully accepted by the user, which leads to CF between users and designers. However, users and designers hope that they are the winners of the product image perception evaluation, thus forming a cognitive game between cognitive subjects. Only by balancing CF can the purpose of balancing cognitive games be achieved, and finally the new product's design and development will be more successful. This paper builds a balance model of CF based on game theory and obtains more objective and accurate assessment information to complete the evaluation of product image form and provide designers with a cognitive basis for further product design.

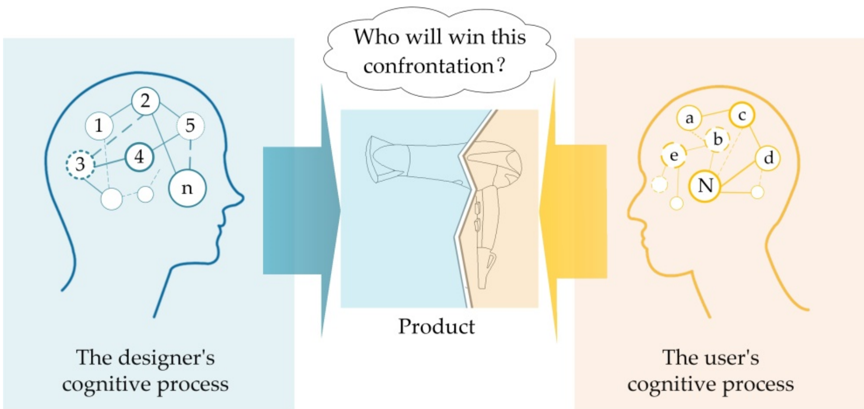

Figure 3. Schematic diagram of the cognitive game process.

3. Method

By combining qualitative and quantitative research methods, we establish the flow of the entire study, as shown in Figure 4, including the product form image evaluation, the establishment and application of CF evaluation model and balance model, and the model verification. First, the collection of picture samples was carried out in various ways and combined with morphological similarity evaluation, to obtain the research sample set. Second, the image vocabulary corresponding to this product was collected on the Internet, and the target image vocabulary was obtained through the SD and image entropy method. Next, based on the target image, fuzzy Theil entropy was used to calculate the CF between users and designers, and the samples were sorted and analyzed based on the size of the index. Then, the CF balance model was established based on the game theory equilibrium thought, to obtain the comprehensive evaluation value of the product form under the target image. Finally, the eye-tracking experiment was used to verify the feasibility of the model.

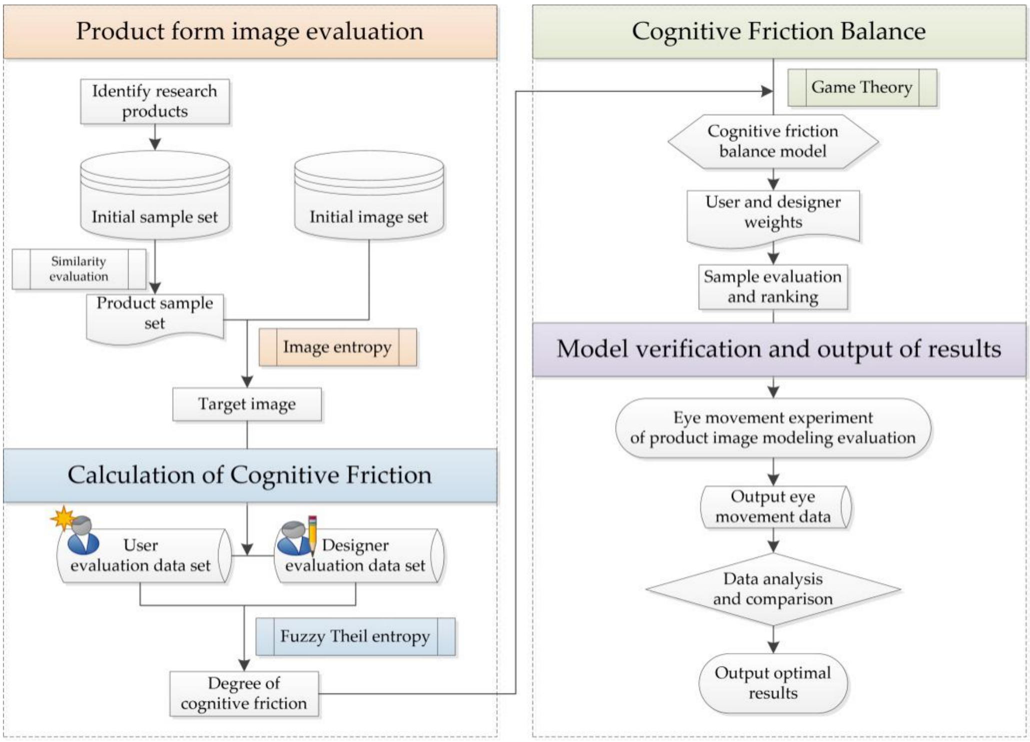

Figure 4. Research framework.

3.1. Evaluation of Product form Image

The image is the main form of thinking activity, and it is the conscious activity of the object within the cognitive subject. The image of product form is the language used by the cognitive subject to communicate with the product on the product form, color structure, etc., and is the driving force and direction of the optimal design of the product form. The accuracy of image extraction is related to whether designers and enterprises can effectively design and develop products that meet the user's emotional and functional requirements [45]; in short, its accuracy is directly related to the success or failure of product development. However, due to differences in knowledge background, cognitive thinking, etc., designers and users will have cognitive differences at the cognitive level of the same product [46], thereby leading to CF in the human–machine environment. The target image represents the main evaluation of the product form by the cognitive subject. In an ideal design activity, only when the designer fully understands the user's target image can he/she formulate the corresponding design strategy to match his/her own cognition and the user's cognition and form a state of cognitive equilibrium. At present, researchers usually use the oral analysis method, image scale method, physiological experiment method, etc., to mine the target image of the cognitive subject to the product.

Entropy, as an important indicator in measuring the stability of the system, refers to the degree of system chaos, that is, a measure of the probability of the system when it is in a certain state. The greater the system entropy value is, the greater the probability of being in this state. Information entropy theory was first introduced by Shannon, in the field of thermodynamics [42], as a measure of the negative entropy of the amount of information, indicating the degree of order of the system and reflecting the degree of diversity of the dataset. The greater the degree of diversity is, the greater the weight value of the standard, and conversely, the smaller the weight value. In this paper, based on the principle of information entropy, the evaluation data of users and designers are calculated to obtain the image entropy value of the sample being evaluated, thereby obtaining the weight of each image in the image set. The image with the largest weight value is selected as the target image in this paper. The product target image value represented by the entropy value is as follows:

$$\chi_j = -\sigma \sum_{i=1}^{m} \left(P_{ij} \ln P_{ij} \right) \tag{1}$$

where χ_j represents the image entropy value; i represents the research sample set, i = 1, 2, 3, ... , m; j represents the initial target image set, j = 1, 2, 3, ... , n; P_{ij} represents the probability of the j-th image of the i-th product sample, $0 \leq P_{ij} \leq 1$; σ is a constant; and $\sigma = 1/\ln m$.

The SD method is widely used to quantify the perception of cognitive subjects and is generally divided into five and seven-level evaluations. The five-level evaluation process is shown in Figure 5.

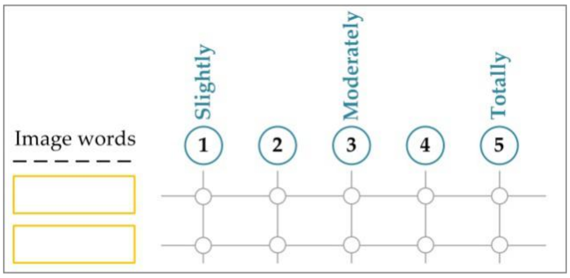

Figure 5. Five-level SD evaluation process.

The five-level SD method is used to evaluate user and designer product image forms in this paper, and an evaluation matrix is established as follows:

$$X^{\Theta} = \begin{bmatrix} X_{11}^{\Theta} & X_{12}^{\Theta} & \cdots & X_{1n}^{\Theta} \\ X_{21}^{\Theta} & X_{22}^{\Theta} & \cdots & X_{2n}^{\Theta} \\ \vdots & \vdots & X_{ij}^{\Theta} & \vdots \\ X_{m1}^{\Theta} & X_{m2}^{\Theta} & \cdots & X_{mn}^{\Theta} \end{bmatrix} \tag{2}$$

where Θ represents the cognitive subject; Θ = 1,2 represents the user and designer, respectively; and X_{ij}^{Θ} represents the evaluation value of the j-th image of the i-th sample by the Θ-type cognitive subject.

To reduce the error of the cognitive subject in the evaluation process, the evaluation matrix, X^{Θ}, is normalized to obtain the image decision matrix, $\breve{X}^{\Theta}$, and then the probability P_{ij} of the image is obtained as follows:

$$P_{ij} = y_{ij} \bigg/ \sum_{j=1}^{n} \left(1 - \chi_j \right) \tag{3}$$

where y_{ij} is the normalized data of the j-th image of the i-th sample.

Using Formula (1) to calculate the probability P_{ij} of each image to obtain the entropy value of the j-th image, we see the weight W_j of the image in the entire evaluation process is as follows:

$$W_j = \left(1 - \chi_j \right) \bigg/ \sum_{j=1}^{n} \left(1 - \chi_j \right) \tag{4}$$

According to the weight value of each image, the largest image is selected as the target image of this study.

3.2. Evaluation of CF

Due to differences in knowledge, experience, environment, etc., for the same product, the perception model generated by the user is different from that of the designer. Though users focus on the function, appearance, manner of use, etc., the designer is concerned with the imagery feeling, such as inspiration, beauty, and experience, which is the designer's invisible knowledge. This causes CF between them. In the actual design process, only when the designer conducts in-depth research on the user's perception and accurately grasps the user's perceptual knowledge can the design scheme be successful, thereby improving design efficiency. Therefore, the first step of design is to evaluate the CF between the user and designer so that the designer can grasp the difference and size of his/her cognitive difference with the user. It is convenient for designers to adjust the design ideas in time, to achieve cognitive symmetry with users.

Theil entropy, also known as the Theil index, is a statistic used by the Dutch economist Theil in 1967 to measure economic inequality [47] and is also commonly used in econometrics as a measure of relative difference. It is commonly used as an assessment of regional development differences, also known as inequality. The larger the value is, the greater the difference in development. This indicator usually represents the inequality between the subgroups of a group in the form of a weighted sum. According to the demand, it can also be decomposed to obtain the measurement of the contribution of intragroup and intergroup differences to system differences and to reveal the impact of intragroup and intergroup differences on the entire system.

According to the needs of this research, the fuzzy Theil entropy value is used to characterize the CF of the two groups of users and designers on the same product; that is, fuzzy Theil entropy is used to represent CF. For sample i, the expression of the Theil entropy index is as follows:

$$T^i = (X_i^1/X_i^1 + X_i^2) \ln \frac{(X_i^1/\alpha)(\alpha+\beta)}{(X_i^1 + X_i^2)} + (X_i^2/X_i^1 + X_i^2) \ln \frac{(X_i^2/\beta)(\alpha+\beta)}{(X_i^1 + X_i^2)} \tag{5}$$

where X_i^1 and X_i^2 represent the sum of the evaluation values of all users and designers on sample i, respectively; and α and β represent the number of users and designers, respectively.

For sample i, the CF F_r^i between users and designers is as follows:

$$F_r^i = T^i \bigg/ \sum_{i=1}^{m} T^i \tag{6}$$

3.3. Construction of the CF Balance Model

In Section 3.2, we evaluated the value of CF. To achieve cognitive balance in the evaluation process of sample modelling images, we establish a CF balance model. In the above sections, we introduced game theory in detail. Because of its obvious advantages in balancing decision-making, this paper builds a CF balance model based on game theory. The cognitive weights of users and designers are participants, and the final comprehensive weight vector is a balanced decision. Then, we proceed as follows:

Step 1: According to the evaluation value of the target image of the sample product by the user and designer, cognitively weight the user and designer to obtain the basic weight vector set $\lambda = \{\lambda_1, \lambda_1, \ldots, \lambda_k\}(k = 1, 2, \ldots, m)$.

$$\lambda_i = \left(\frac{X_i^1}{X_i^1 + X_i^2}, \frac{X_i^2}{X_i^1 + X_i^2} \right) \tag{7}$$

Mark any linear combination of m different vectors, as follows:

$$\lambda = \sum_{k=1}^{m} \omega_k \lambda_k^T \tag{8}$$

where $\omega_k > 0, \sum_{k=1}^{m} \lambda_k = 1$, λ is any possible weight vector in the weight set, and ω_k is the linear combination coefficient.

Step 2: Optimize m linear combination coefficients ω_k by applying game theory to minimize the deviation between λ and each λ_k, as follows:

$$\min \left\| \sum_{k=1}^{m} \omega_k \lambda_k^T - \lambda_\eta \right\|_2 (\eta = 1, 2, \ldots, m) \tag{9}$$

According to the differential properties of the matrix, Equation (10) can be used to express the optimal first derivative condition in Equation (9):

$$\sum_{k=1}^{m} \omega_k \lambda_\eta \lambda_k^T = \lambda_\eta \lambda_\eta^T (\eta = 1, 2, \ldots, m) \tag{10}$$

Converting it to a linear formula, Formula (11) is as follows:

$$\begin{bmatrix} \lambda_1\lambda_1^T & \lambda_1\lambda_2^T & \cdots & \lambda_1\lambda_m^T \\ \lambda_2\lambda_1^T & \lambda_2\lambda_2^T & \cdots & \lambda_2\lambda_m^T \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_m\lambda_1^T & \lambda_m\lambda_2^T & \cdots & \lambda_m\lambda_m^T \end{bmatrix} \begin{bmatrix} \omega_1 \\ \omega_2 \\ \vdots \\ \omega_m \end{bmatrix} = \begin{bmatrix} \lambda_1\lambda_1^T \\ \lambda_2\lambda_2^T \\ \vdots \\ \lambda_m\lambda_m^T \end{bmatrix} \tag{11}$$

Step 3: Calculate $(\omega_1, \omega_2, \ldots, \omega_m)$ through Formula (11), and normalize it to obtain the following:

$$\omega_k^* = |\omega_k| \Big/ \sum_{k=1}^{m} |\omega_k| \tag{12}$$

Therefore, the most satisfying user and designer cognitive weight vectors are as follows:

$$\omega^* = \sum_{k=1}^{m} \omega_k^* \omega_k^T \tag{13}$$

According to ω^*, the evaluation value of each sample image form based on CF balance can be calculated as follows:

$$X_i = \sum_{\Theta=1}^{2} \omega_\Theta^* X_i^\Theta \tag{14}$$

Therefore, according to the size of X_i, the sample image form after the CF balance can be sorted.

3.4. Model Verification

To verify the reliability of the CF balance model, an eye-tracking experiment is used to evaluate the results. The entire verification process is completed based on the stages, like experimental design, eye-tracking-equipment calibration, and data output and analysis. Finally, there comes an optimal evaluation result through comparison.

4. Case Study

According to market research, this paper verified the feasibility of the CF evaluation method and balance model through the image form evaluation of household hair dryers. The model method is also applicable to other products.

4.1. Determination of the Sample and Its Target Image

Combined with the hair dryer, a total of 128 sample pictures were collected from product sales websites, periodicals, etc. The authoritative designer conducted a preliminary screening from the form, brand, and other aspects, and obtained a total of 36 initial sample sets. To avoid the influence of external factors such as color and brand, line manuscript processing and numbering were used. Then, the SD method was used to create a product form similarity evaluation questionnaire. Twenty-eight students majoring in design conducted form similarity evaluation, and the K-means clustering method was used to cluster the evaluation results. Thirty-six sample images were clustered into 12 categories, and the clustering results are shown in Table 1. The sample closest to the clustering center of each cluster from each category was selected as a representative to form a research sample set, as shown in Figure 6.

Table 1. Initial sample clustering results.

Category	Sample	Category	Sample	Category	Sample
1	12,13*,14	5	33*	9	30*
2	2,18,19,20, 21*,22,23,34	6	6*	10	10,29*
3	3*,7,25,26	7	24,28*,35,36	11	8,9,16,17*,31
4	4*	8	32*	12	1*,5,11,15,27

Selected samples are marked with "*".

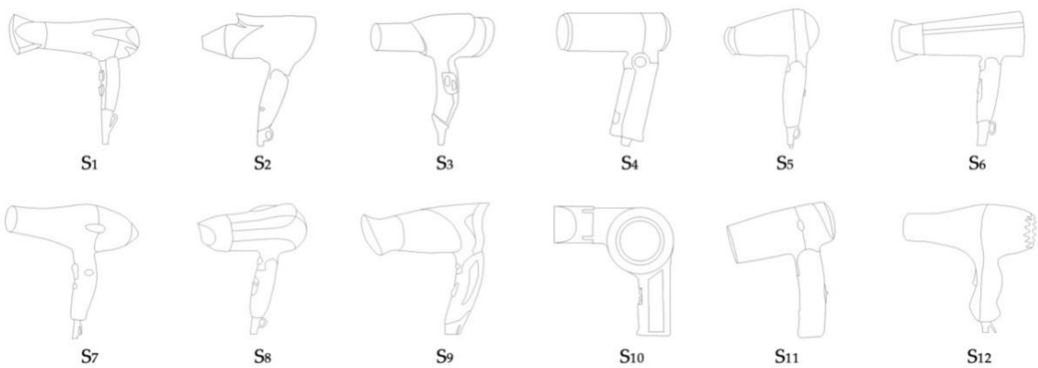

Figure 6. Study sample set.

According to the evaluation of users on the hair-dryer sales website, the initial target image vocabulary of this study is extracted as follows: "Simplicity", "Streamlined", "Individuality", "Holistic", "Advanced", and "Useful". To ensure the fairness and rationality of designers and users in the evaluation process, eight designers, each with experience in hair-dryer-form design, and users, each with experience in the frequent use of hair dryers, were selected to form two types of cognitive subjects. A five-level SD questionnaire was used to construct the evaluation process of cognitive subjects. Before the evaluation began, the purpose of the study and the evaluation process were fully explained to the participants, and the evaluation experiment was started after obtaining their consent or confirmation. To ensure that the evaluation results of the participants were not affected by the order of the samples, in the design of the SD questionnaire, the order in which the samples appeared was set to be random, thus ensuring the maximum scientific accuracy of the evaluation results. The evaluation results are shown in Table 2.

Table 2. Evaluation values of the initial target image of the product samples.

	Simplicity	Streamlined	Individuality	Holistic	Advanced	Useful
S_1	2.50	4.00	2.88	1.81	3.06	2.75
S_2	3.38	3.13	3.56	2.69	2.50	2.69
S_3	3.25	2.69	2.63	2.06	2.63	3.06
S_4	4.13	1.50	3.13	3.13	2.13	3.19
S_5	4.19	2.38	2.00	3.69	2.31	3.81
S_6	3.44	1.88	2.63	3.13	2.44	3.50
S_7	3.56	3.56	2.38	3.19	3.00	3.69
S_8	2.19	3.75	3.81	1.63	2.63	3.00
S_9	2.19	3.75	3.69	1.63	2.25	2.44
S_{10}	2.69	1.94	3.06	3.38	2.75	2.31
S_{11}	3.69	1.81	2.38	4.19	2.94	2.94
S_{12}	4.50	1.38	3.56	4.06	3.94	4.06

From Table 2, the weight value of each image vocabulary was obtained by using Formulas (3) and (4), as shown in Figure 7. It can be seen from the results that the "Holistic" image weight is higher, while the "Individuality" image weight is lower. Therefore, "Holistic" is selected as the target image of this paper.

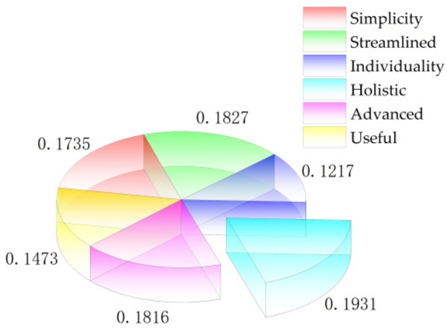

Figure 7. Weighted values of each image vocabulary.

4.2. *Research on CF Evaluation Based on Target Image*

Eight experienced designers and eight typical users were selected as the expert group to evaluate the target image of the research samples, and the evaluation results are shown in Table 3. According to Formulas (5) and (6), the degree of CF between two cognitive subjects can be seen in Figure 8.

Table 3. Evaluation results of users and designers.

Sample	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}	S_{11}	S_{12}
Au	2.13	2.63	2.13	3.00	3.88	3.38	3.00	2.13	1.88	3.88	4.63	4.00
Su	17	21	17	24	31	27	24	17	15	31	37	32
Ad	1.50	2.75	2.00	3.25	3.50	2.88	3.38	1.13	1.38	2.88	3.75	4.13
Sd	12	22	16	26	28	23	27	9	11	23	30	33

Au represents the average of user evaluation values; Su represents the sum of user evaluation values; Ad represents the average of designer evaluation values; Sd represents the sum of designer evaluation values.

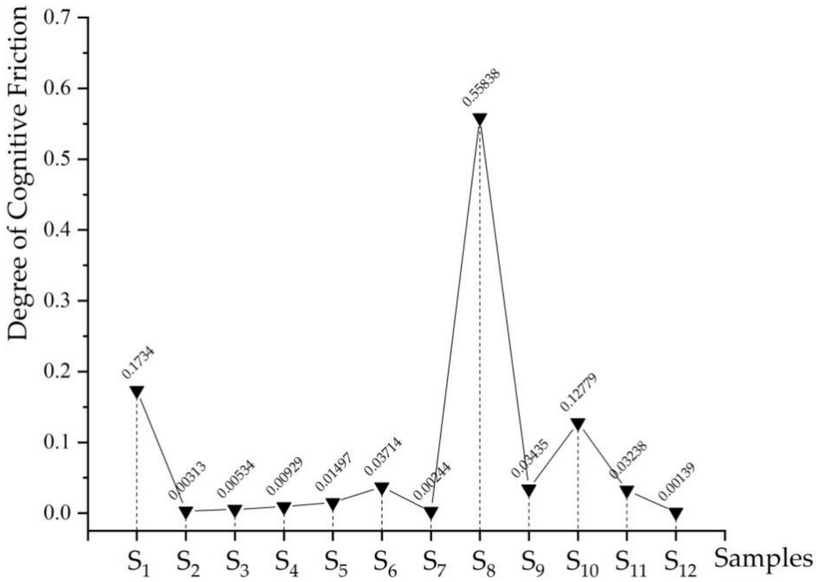

Figure 8. Degree of CF between cognitive subjects, based on target image.

According to Figure 8, the smallest CF value of 0.00139 is obtained for sample S_{12}, while the largest is obtained for sample S_8. The degree of CF is ranked as follows: $S_8 > S_1 > S_{10} > S_6 > S_9 > S_{11} > S_5 > S_4 > S_3 > S_2 > S_7 > S_{12}$.

4.3. Research on CF Balance

According to the CF balance model constructed in Section 3.3, by using Formula (7), the calculated λ results based on the evaluation data of users and designers are shown in Table 4. Then, the cognitive weight vector of users and designers is obtained as 0.56 and 0.44, respectively, by using Formulas (8)–(13). The comprehensive evaluation value of each sample based on the target image was calculated by Formula (14), which is shown in Table 5.

Table 4. λ value.

λ_1	λ_2	λ_3	λ_4	λ_5	λ_6
(0.59,0.41)	(0.49,0.51)	(0.52,0.48)	(0.48,0.52)	(0.53,0.47)	(0.54,0.46)
λ_7	λ_8	λ_9	λ_{10}	λ_{11}	λ_{12}
(0.47,0.53)	(0.65,0.35)	(0.58,0.42)	(0.57,0.43)	(0.55,0.45)	(0.51,0.49)

Table 5. Comprehensive evaluation values of samples.

S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}	S_{11}	S_{12}
1.85	2.68	2.07	3.11	3.71	3.16	3.17	1.69	1.66	3.44	4.24	4.06

Combined with the original evaluation data of users and designers, the sample order after CF balance is shown in Figure 9. It can be seen from the figure that the original evaluation value contains two cognitive subjects of the user and the designer, and there is a large gap of the evaluation value among some samples, such as S_1, S_8, S_{10}, and S_{11}. This leads to the asymmetry of cognitive information in the evaluation process of product samples and makes decision makers unable to obtain effective evaluation information accurately. After the evaluation of the quantitative CF balance model, the evaluation information of users and designers can be calculated reasonably and comprehensively, and each sample can obtain comprehensive evaluation results, which makes the evaluation information of the sample target image more accurate and reasonable, and improves the efficiency of decision-making.

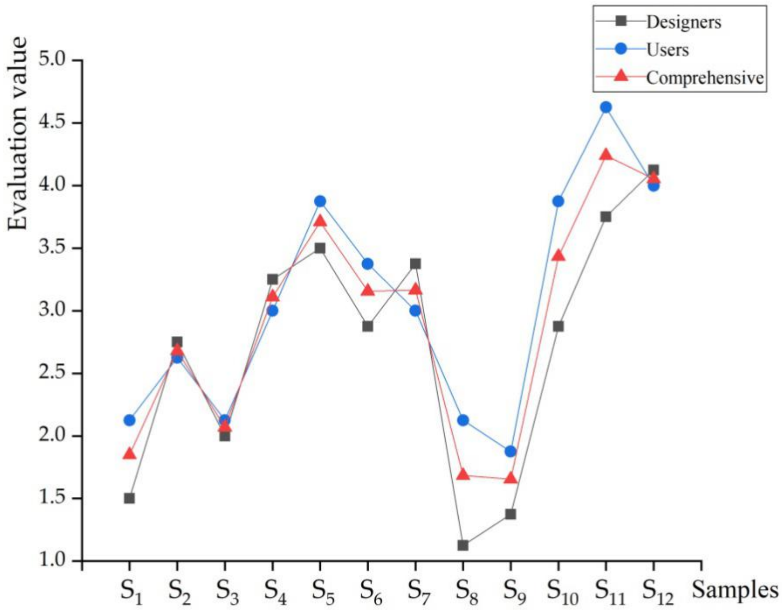

Figure 9. Comparison of the evaluation of sample image form.

For all samples, the comprehensive evaluation value of sample S_{11} is the highest, which is 4.24; S_9 is the lowest, which is 1.66. The ranking of all comprehensive evaluations is as follows: $S_{11} > S_{12} > S_5 > S_{10} > S_7 > S_6 > S_4 > S_2 > S_3 > S_1 > S_8 > S_9$. For sample S_{11}, its user evaluation value has an absolute advantage in all samples, while the user evaluation value of S_9 is the lowest, which shows that the user evaluation participation is essential in the early stage of product development.

4.4. Result Verification

To increase the credibility of the comprehensive evaluation results, we used the eye movement experiment [48] for verification. The experiment uses a Tobii X2-30 eye tracker with the ErgoLAB software installed on an ASUS 14-inch display for the experimental process and data processing analysis.

During the design of the experiment, samples S_1~S_{12} were uniformly sized and put into the experimental material with a white background. Each sample was preset as an area of interest (AOI), and then a total of 12 AOIs were formed in the experimental material: AOIS1, AOIS2, AOIS3, AOIS4, AOIS5, AOIS6, AOIS7, AOIS8, AOIS9, AOIS10, AOIS11, and AOIS12, as shown in Figure 10. Five graduate students (with both design-thinking and product-use experience) were randomly selected from the design profession as participants to participate in the experiment, including 3 males and 2 females, all without colour blindness and colour weakness and with corrected vision of 1.0 and above. To ensure the reliability of the experimental results, before the start of the experiment, only the experimental operation process was trained, and the participant of the experiment was not informed. The experiment guideline was set as follows: "please select the sample you think is the most "Holistic" and tap "space" to go to the next page". The experimental process is shown in Figure 11.

Figure 10. Areas of interest (AOIs) of the sample.

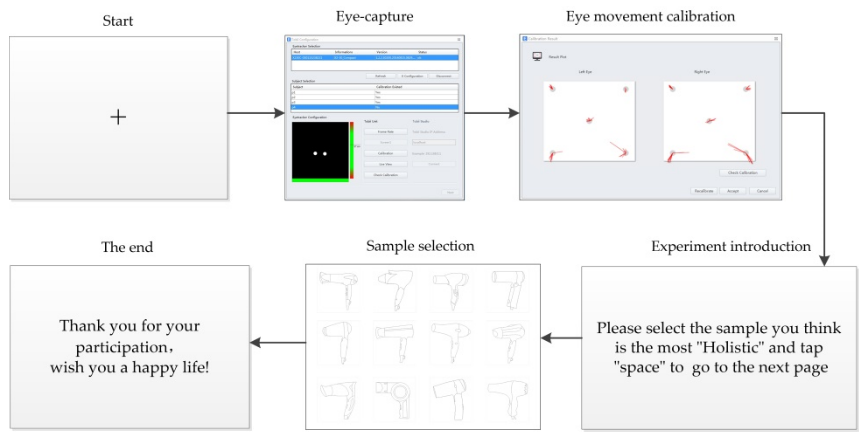

Figure 11. Flow of eye movement experiment (during the actual experiment, the introduction and end are expressed in Chinese).

Five participants completed the experiment in turn and received a small gift as a reward. The “Time to First Fixation”, “Fixation Duration”, and “Fixation Count” were taken in AOI as statistical objects. According to the recorded data of ErgoLAB, for all AOIs, the final statistical results are shown in Figure 12. It can be seen from the comprehensive data in the figure that, for the “Time to First Fixation” of AOI, sample S_{12} is the highest. However, comparing the “Fixation Duration” and “Fixation Count” of each participant and the total, we see sample S_{11} is much more concerning than sample S_{12}. This shows that, when looking at the sample for the first time, sample S_{12} will be attractive, but after repeated comparisons, most of the participants will finally choose sample S_{11} as the sample that is most “Holistic”. This conclusion can also be drawn from the eye movement trajectory of Figure 13 and the heat map of Figure 14, which is consistent with the comprehensive evaluation results in Section 4.3. Therefore, the balance model of CF is effective and feasible in the actual evaluation process. In the subsequent design of the form of the hair dryer, sample S_{11} can be used as a design reference for the “Holistic” target image.

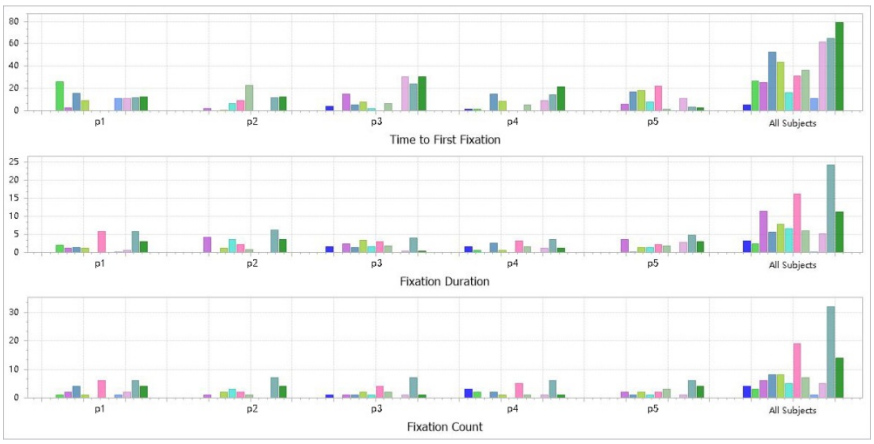

Figure 12. Eye movement data statistics.

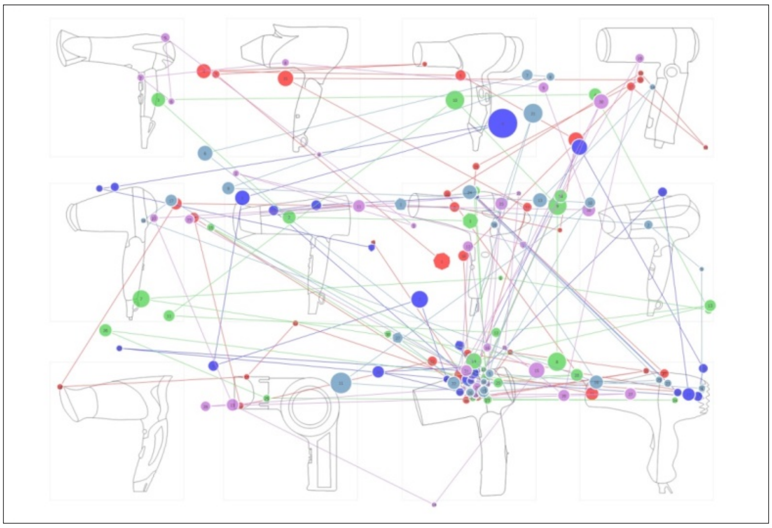

Figure 13. Eye movement trajectories.

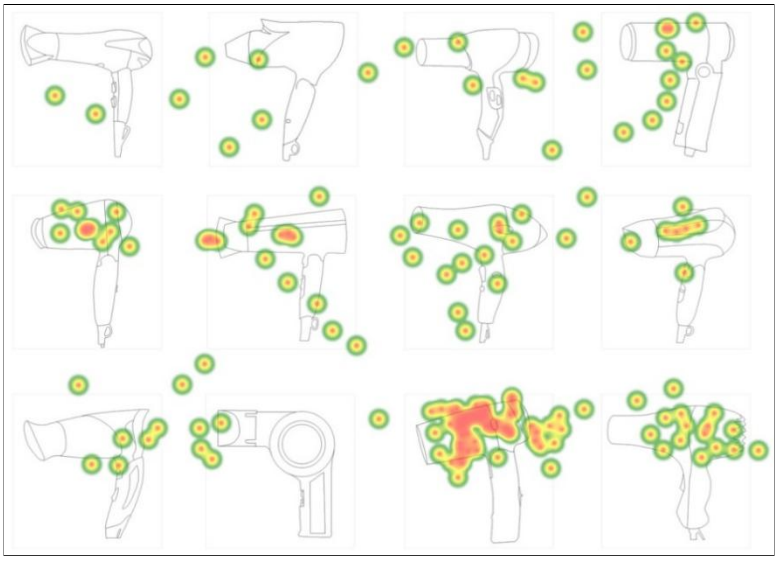

Figure 14. Eye movement heat map.

5. Discussion

5.1. Evaluation of the Paper Results

It can be seen from the results that the best reference of the designer's sample S_{12} has a significant cognitive gap with the user's sample S_{11} as being the most holistic image. Research on the CF balance is a necessary step in the product development process. After comprehensive evaluation, sample S_{11} with the highest value is obtained as the main reference sample for the form design based on the target "Holistic" image. The detailed analysis shows that the designers judge that sample S_{12} has a more holistic nature through the unity of form and the lack of excessive decorative lines on the surface. However, the user thinks that the tail of sample S_{12} is more fragmented, and its functionality is weaker, while the overall appearance of sample S_{11} is clean and tidy, with a more holistic image. Therefore, designers often combine their own experience to pay attention to the overall feeling of the product in the evaluation process, while users pay more attention to details and functions.

From the perspective of CF evaluation, sample S_8 has the largest CF, which is much higher than that of the other samples. However, it can be seen from the final comprehensive evaluation value that the evaluation value of sample S_8 is not the lowest, and although the CF of sample S_{12} is the smallest in the entire evaluation sample set, this is not the case in the final preferred sample. Therefore, it can be considered that it is not that the CF between cognitive subjects is as small as possible in the design process. CF can be used only as a reference in the image evaluation process, and the preferred sample will appear at the minimum value of nearby CF. A question for future research is as follows: What is the specific range of CF that is more in line with the evaluation criteria? Similarly, in the research on CF balance, game theory has played an important role in establishing a balance model, which also illustrates the feasibility and necessity of using game theory in cognitive science research.

5.2. Evaluation of the CF

Due to the difference in professional background and thinking styles between cognitive subjects, different cognitive subjects have obvious differences in perception and expression of product characteristics when designing products, which leads to the asymmetry of cognitive information. The concept of CF was presented to intuitively show the differentiation. However, the existing literature [9,10,49] only quotes the concept of CF, and the actual research is still on cognitive asymmetry, which is not expressed at a quantitative level, so the assessment of CF remains at a qualitative level. The size of CF and the mechanism of its generation are still unobservable and predictable. For designers, it is still impossible to accurately grasp the cognitive asymmetry between the product design process and the user. This research is a further study of CF, using fuzzy Theil entropy to quantitatively calculate the size of CF, so the cognitive subject can intuitively feel the asymmetry, and it can provide theoretical guidance for designers in the product design process.

5.3. Cognitive Symmetry

In the field of product design, the cognitive balance between cognitive subjects is an essential research step, which is called "cognitive symmetry". Only after the cognition between cognitive subjects reaches symmetry can designers grasp the emotional needs of users or other cognitive subjects more accurately, and thus complete product development more efficiently. The research of user needs is the first step of product development plan, and the designer is both the implementer of research and the undertaker of design work. Therefore, both the user and the designer play an indispensable role in the product design. Comprehensive user's emotional needs and designer's design thinking or experience are necessary to guarantee the success of product development. Though Quan et al. [29] combined Kansei engineering and game theory methods to complete product recommendations to users, they did not take the designer into account, so the cognitive subject was relatively single. Su et al. [42] took the perceptual cognition of users, designers, and engineers into consideration, but they used a more subjective AHP method in the process of cognitive balance. Similarly, Yang et al. [38] used the subjective form of questionnaires and interviews to comprehensively evaluate the cognitive differences between designers and users. This paper comprehensively considers the cognitive differences between users and designers. Based on the advantages of game theory in system evolution and balance, we establish a cognitive balance model between cognitive subjects and complete a quantitative cognitive symmetry study, which makes the evaluation process more reasonable.

6. Conclusions

In order to realize the symmetry and balance between cognitive subjects (users and designers) and achieve the purpose of comprehensive evaluation of product image forms among different cognitive subjects, this paper proposes a CF evaluation and balance model combining fuzzy Theil entropy and game theory to obtain the product form under the target image, and the evaluation results are verified by eye movement experiments. First, a CF evaluation system is established based on image entropy and fuzzy Theil entropy, and the CF between users and designers is evaluated for the samples. Then, combined with game theory ideas, a cognitive friction balance model is constructed, comprehensive evaluation weights between cognitive subjects are obtained, and sample forms are comprehensively sorted. This paper takes the form of a household hair dryer as an example to verify the effectiveness and feasibility of the entire process. Compared with current researches, this paper adopts a new theoretical method to quantify the CF at a perceptual level and visually demonstrate it. With the advantages in system evolution and balance, the game theory is applied to the comprehensive evaluation of the weight between cognitive subjects to obtain the target image form more accurately and efficiently. The main conclusions are as follows. (1) Through the calculation of fuzzy Theil entropy, the evaluation of CF between users and designers is completed. In the design process, designers can grasp the cognitive asymmetry with users quantitatively and improve the design efficiency and product development success rate. (2) Game theory, as the thinking of balancing the pursuit of optimal expectations by both parties of interest, can be effectively used to establish a CF model between balancing cognitive subjects to achieve cognitive symmetry and then achieve the purpose of balancing cognitive differences. This also introduces new thinking and methods for cognitive science research. (3) The research on the evaluation and balance of CF provides a certain research method for grasping and predicting emotional preferences in product intelligent design. The shortcomings and prospects of this research are listed as follows. (1) This paper defines only cognitive subjects as users and designers, but in the actual product life cycle, cognitive subjects also include engineers, decision makers, and product recyclers. The application of the CF evaluation and balance model on multiple cognitive subjects is not verified in this paper. (2) In order to mine the intuitive feelings of users and designers, the evaluation data of this paper were obtained by using the five-level SD method, which is relatively simple to acquire. In the future, we will consider using a combination of physiological measurement and psychological evaluation to obtain relevant objective data. In this paper, only the form of the product is considered, but in the actual product design process, color is also one of the important design elements. In the following research, the coupling game of product form and color will be our work. By relying on the advantages of game theory in system evolution and balance, we will establish a coupled game model of product form and color to build a product form color-matching system under the target image.

Author Contributions: Conceptualization, J.S. and K.Q.; methodology, K.Q. and X.Z.; validation, W.Y.; data curation, K.Q.; writing—original draft preparation, K.Q. and X.Z.; writing—review and editing, K.Q. and J.S. All authors have read and agreed to the published version of the manuscript.

Funding: The project is sponsored by National Natural Science Foundation of China (51465037), Hongliu Outstanding Talent Development Program of Lanzhou University of Technology (J201406).

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Kim, W.; Ko, T.; Rhiu, I.; Yun, M.H. Mining affective experience for a kansei design study on a recliner. *Appl. Ergon.* **2019**, *74*, 145–153. [CrossRef] [PubMed]
2. Maleki, S.; Amiri Aghdaie, S.F.; Shahin, A.; Ansari, A. Investigating the relationship among the Kansei-based design of chocolate packaging, consumer perception, and willingness to buy. *J. Mark. Commun.* **2019**, 1–20. [CrossRef]
3. Srivastava, N.; Hinton, G.; Krizhevsky, A. Dropout: A Simple Way to Prevent Neural Networks from Overfitting. *J. Mach. Learn. Res.* **2014**, *15*, 1929–1958.
4. Wang, Y.; Mo, D.Y.; Tseng, M.M. Mapping customer needs to design parameters in the front end of product design by applying deep learning. *CIRP Ann.* **2018**, *67*, 145–148. [CrossRef]
5. Chen, J.; Luo, N.; Liu, Y.; Liu, L.; Zhang, K.; Kolodziej, J. A hybrid intelligence-aided approach to affect-sensitive e-learning. *Computing* **2016**, *98*, 215–233. [CrossRef]
6. Kapoor, A.; Burleson, W.; Picard, R.W. Automatic prediction of frustration. *Int. J. Hum. Comput. Stud.* **2007**, *65*, 724–736. [CrossRef]
7. Chai, C.; Liao, J.; Zou, N.; Sun, L. A one-to-many conditional generative adversarial network framework for multiple image-to-image translations. *Multimed. Tools Appl.* **2018**, *77*, 22339–22366. [CrossRef]
8. Bertola, P.; Teixeira, J.C. Design as a knowledge agent: How design as a knowledge process is embedded into organizations to foster innovation. *Design Stud.* **2003**, *24*, 181–194. [CrossRef]

9. Feng, Y.X.; Lou, S.H.; Wang, X.P.; Zheng, H.; Gao, Y.C.; Wang, Y.; Tan, J.R. Research on Performance-oriented Perceptual Image Evaluation Method for Cus Tomized Products. *J. Mech. Eng.* **2020**, *56*, 181–190.
10. Ehrensberger, D.M.; O'Brien, S. Ergonomics of the translation workplace: Potential for cognitive friction. *Transl. Spaces* **2015**, *4*, 98–118. [CrossRef]
11. He, C.X. Analysis of Cognitive Friction in Product Design and Use Process. *Packag. Eng.* **2010**, *31*, 58–60.
12. Henson, B.; Barnes, C.; Livesey, R.; Childs, T.; Ewart, K. Affective Consumer Requirements: A Case Study of Moisturizer Packaging. *Concurr. Eng.* **2006**, *14*, 187–196. [CrossRef]
13. Nagamachi, M. Kansei Engineering: A new ergonomic consumer-oriented technology for product development. *Int. J. Ind. Ergon.* **1995**, *15*, 3–11. [CrossRef]
14. Zhang, X.; Yang, M.; Su, J.; Yang, W.; Qiu, K. Research on product color design decision driven by brand image. *Color Res. Appl.* **2020**, 1–15. [CrossRef]
15. Ding, M.; Bai, Z. Product color emotional design adaptive to product shape feature variation. *Color Res. Appl.* **2019**, *44*, 811–823. [CrossRef]
16. Köhler, M.; Falk, B.; Schmitt, R. Applying Eye-Tracking in Kansei Engineering Method for Design Evaluations in Product Development. *Int. J. Affect. Eng.* **2015**, *14*, 241–251.
17. Zhang, X.X.; Yang, M.G. Color image knowledge model construction based on ontology. *Color Res. Appl.* **2019**, *44*, 651–662. [CrossRef]
18. Kristian, P.; Tanel, M.; Andres, K. Considering Emotions in Product Package Design through Combining Conjoint Analysis with Psycho Physiological Measurements. *Procedia–Soc. Behav. Sci.* **2014**, *148*, 280–290.
19. Huang, Y.; Chen, C.H.; Wang, I.H.; Khoo, L.P. A product configuration analysis method for emotional design using a personal construct theory. *Int. J. Ind. Ergonom.* **2014**, *44*, 120–130. [CrossRef]
20. Wang, Z.; Liu, W.; Yang, M.; Han, D. A Multi-Objective Evolutionary Algorithm Model for Product Form Design Based on Improved SPEA2. *Appl. Sci.* **2019**, *9*, 2944. [CrossRef]
21. Yuan, G.S.; Xie, Q.S.; Pan, W.J. Color design based on Kansei engineering and interactive genetic algorithm. *AJME Acad. J. Manuf. Eng.* **2017**, *15*, 12–18.
22. Guo, F.; Li, F.; Nagamachi, M.; Hu, M.; Li, M. Research on color optimization of tricolor product considering color harmony and users' emotion. *Color Res. Appl.* **2020**, *45*, 156–171. [CrossRef]
23. Ding, L.; Che, J.M.; Dong, X.F. Product Bionics Form Design Based on Users' Kansei Image. *Appl. Mech. Mater.* **2010**, *37–38*, 910–914. [CrossRef]
24. Ho, C.H.; Lu, Y.N. Can pupil size be measured to assess design products? *Int. J. Ind. Ergonom.* **2014**, *44*, 436–441. [CrossRef]
25. Jiao, Y.; Qu, Q.X. A proposal for Kansei knowledge extraction method based on natural language processing technology and online product reviews. *Comput. Ind.* **2019**, *108*, 1–11. [CrossRef]
26. Chang, Y.M.; Chen, C.W. Kansei assessment of the constituent elements and the overall interrelations in car steering wheel design. *Int. J. Ind. Ergonom.* **2016**, *56*, 97–105. [CrossRef]
27. Zhou, L.; Xue, C.Q.; Tang, W.C.; Li, J.; Niu, Y.F. User Perceptual Prediction Model of Product Information Interface. *Comput. Integr. Manuf. Syst.* **2014**, *20*, 544–554.
28. Zhu, G.N.; Hu, J.; Qi, J.; Gu, C.C.; Peng, Y.H. An Integrated AHP and VIKOR for Design Concept Evaluation Based on Rough Number. *Adv. Eng. Inform.* **2015**, *29*, 408–418. [CrossRef]
29. Quan, H.; Li, S.; Wei, H.; Hu, J. Personalized Product Evaluation Based on GRA-TOPSIS and Kansei Engineering. *Symmetry* **2019**, *11*, 867. [CrossRef]
30. Shieh, M.D.; Li, Y.; Yang, C.C. Comparison of multi-objective evolutionary algorithms in hybrid Kansei engineering system for product form design. *Adv. Eng. Inform.* **2018**, *36*, 31–42. [CrossRef]
31. Quan, H.; Li, S.; Hu, J. Product Innovation Design Based on Deep Learning and Kansei Engineering. *Appl. Sci.* **2018**, *8*, 2397. [CrossRef]
32. Lokman, A.M.; Haron, M.B.; Abidin, S.Z.; Abd Khalid, N.E.; Ishihara, S. Prelude to Natphoric Kansei Engineering Framework. *J. Softw. Eng. Appl.* **2013**, *6*, 638–644. [CrossRef]
33. Wang, T.X.; Zhou, M.Y. A method for product form design of integrating interactive genetic algorithm with the interval hesitation time and user satisfaction. *Int. J. Ind. Ergonom.* **2020**, *76*, 102901. [CrossRef]
34. Deng, L.; Wang, G.H. Application of EEG and Interactive Evolutionary Design Method in Cultural and Creative Product Design. *Comput. Intell. Neurosci.* **2019**, 1–16. [CrossRef] [PubMed]
35. Li, Y.F.; Shieh, M.D.; Yang, C.C. A Posterior Preference Articulation Approach to Kansei Engineering System for Product Form Design. *Res. Eng. Des.* **2019**, *30*, 3–19. [CrossRef]

36. Javad, K.; Owain, P. A semantic discontinuity detection (SDD) method for comparing designers' product expressions with users' product impressions. *Design Stud.* **2019**, *62*, 36–67.
37. Norman, D.A. *The Design of Everyday Things*; CITIC Press Group: Beijing, China, 2003; pp. 17–18.
38. Yang, Y.P.; Liu, Q. Product form design method driven by design intent. *Comput. Integr. Manuf. Syst.* **2015**, *21*, 867–874.
39. Lai, C.; Chen, X.; Chen, X.; Wang, Z.; Wu, X.; Zhao, S. A fuzzy comprehensive evaluation model for flood risk based on the combination weight of game theory. *Nat. Hazards* **2015**, *77*, 1243–1259. [CrossRef]
40. Liu, T.; Deng, Y.; Chan, F. Evidential Supplier Selection Based on DEMATEL and Game Theory. *Int. J. Fuzzy Syst.* **2018**, *20*, 1321–1333. [CrossRef]
41. Zhou, X.; Deng, X.; Deng, Y.; Mahadevan, S. Dependence assessment in human reliability analysis based on D numbers and AHP. *Nucl. Eng. Des.* **2017**, *313*, 243–252. [CrossRef]
42. Su, J.N.; Zhang, X.X.; Jing, N.; Chen, X. Research on the entropy evaluation of product styling image under the cognitive difference. *J. Mach. Des.* **2016**, *33*, 105–108.
43. Li, L.H.; Mo, R. Production Task Queue Optimization Based on Multi-Attribute Evaluation for Complex Product Assembly Workshop. *PLoS ONE* **2015**, *10*, e0134343. [CrossRef] [PubMed]
44. Zhao, H.; Li, N. Optimal Siting of Charging Stations for Electric Vehicles Based on Fuzzy Delphi and Hybrid Multi-Criteria Decision Making Approaches from an Extended Sustainability Perspective. *Energies* **2016**, *9*, 270. [CrossRef]
45. Yang, C.C. A Classification-Based Kansei Engineering System for Modeling Consumers' Affective Responses and Analyzing Product Form Features. *Expert Syst. Appl.* **2011**, *38*, 11382–11393. [CrossRef]
46. Wang, L.; Cao, Q.; Mo, X. Study of Users' Kansei on Commercial Aircraft Cockpit Interior Design. *J. Mech. Eng.* **2014**, *50*, 122–126. [CrossRef]
47. Liu, G.; Hu, F.; Wang, Y.; Wang, H. Assessment of Lexicographic Minimax Allocations of Blue and Green Water Footprints in the Yangtze River Economic Belt Based on Land, Population, and Economy. *Int. J. Environ. Res. Public Health* **2019**, *16*, 643. [CrossRef]
48. Guo, G.; Lin, L.; Xu, N. User-perceived styling experience of smart vehicles: A method to combine eye tracking with semantic differences. *IET Intell. Transp. Syst.* **2019**, *13*, 72–78.
49. Chen, M. Research of Design Elements Based on Cognitive Friction. Ph.D. Thesis, Southeast University, Nanjing, China, 6 January 2017.

Bulletin of the JSME Vol.16, No.6, 2022
Journal of Advanced Mechanical Design, Systems, and Manufacturing

Research on product target image cognition based on complex network theory and game theory

Kai QIU*, Jianning SU**, Shutao ZHANG** and Wenjin YANG*
*School of Mechanical & Electronical Engineering, Lanzhou University of Technology
36 Pengjiaping Road, Lanzhou 730050, China
E-mail: sujn@lut.edu.cn
**School of Design Art, Lanzhou University of Technology
287 Langongping Road, Lanzhou 730050, China

Received: 26 April 2021; Revised: 10 November 2021; Accepted: 11 May 2022

Abstract
Customer knowledge of a target image is an important and primary research topic related to the product design and development process. This paper presents research on product target image reasoning based on complex network theory and game theory. First, through an evaluation of the correlations among images, a complex network structure diagram with image words as nodes is constructed, and the network attributes of node degree, betweenness and closeness to the centre of the network are calculated. Then, based on the related methods of game theory, the weights of the three network attributes are evaluated, and a comprehensive calculation is carried out on the image to obtain the target image. Finally, an image entropy algorithm is used to validate the results. Taking a scooter as an example, a complex network of 12 image words is constructed by collecting the evaluations of a total of 12 subjects from different professional fields on 8 scooter samples; thus, the verification of the case is completed. This paper provides a more efficient and accurate target image evaluation method for product design or development, which is a new proposal for the product intelligent design process.

Keywords: Target image, Complex network, Game theory, Network attributes, Image entropy

1. Introduction

Product development technology has greatly improved productivity, but separating the aspects of functional characteristics has been difficult. In a dynamic market environment, product competition changes over time (Xie et al., 2020). In user-oriented markets, it is becoming increasingly urgent to design products that meet customers' needs and their desires for emotional experiences (Kin et al., 2019; Maleki et al., 2019). Product design is a complex activity that is highly dependent on personal impressions, feelings and emotions. Arousing emotional resonance with customers in product design is very important for successful product design (Yeh, 2020). Kansei image demand is an important informational input for the design process (Lin et al., 2020). In the process of design innovation, obtaining customers' Kansei image demands for product design efficiently and accurately determines the direction of product innovation and optimization and the final innovation form and ultimately affects customers' purchase desire and satisfaction (Wang et al., 2020), which is of great significance for effectively stimulating innovative inspiration in the forward design process (Moon et al., 2015). Therefore, it is the first step in product design and development and is important for efficiently and intuitively determining customer image demand.

The complexity and diversity of customers' Kansei images generally means that products have multidimensional Kansei needs (Zhou et al., 2018). Evaluating the weights of multidimensional Kansei images directly affects the accuracy of the product development direction, which makes the efficient and accurate acquisition of initial data extremely important. To solve the problem of customer image demand acquisition and evaluation, researchers have used various complex evaluation methods and data processing models. For example, Wu et al. (2019) objectively determined the relative importance of each emotional demand based on customer positioning, and the key customer demand in product design was identified by using a rough number algorithm. Jiang et al. (2018) took the conceptual design of a transmission

Paper No.21-00155
[DOI: 10.1299/jamdsm.2022jamdsm0062]

device as an example and evaluated the design goal by combining cluster analysis and a cooperative game model. Yao et al. (2016) investigated the mapping mechanism of "image cognition-design features" for bus modelling and established a method to drive bus modelling design feature reasoning with style image cognition demand, which provided a theoretical basis and technical support for specific form design work. All the above studies used qualitative evaluation methods to obtain customer demand data, but the large amount of data can easily make the subjects' judgements of images vague, making the evaluation results highly subjective. To effectively and objectively meet users' demand for Kansei images of products, some researchers have used physiological experiments to obtain customer image evaluation data. Gao et al. (2020) introduced implicit measurement technology into the process of image extraction. By exploring the relationship between cognitive data and product images within users' nonsubjective consciousness, an unconscious multimodal implicit measurement image extraction model based on the combination of an implicit association test and multimodal implicit measurement was established. Yang et al. (2018) used electroencephalography (EEG) experiments to obtain customers' Kansei cognitive data to explore the corresponding relationship between EEG and product images in customers' cognitive processes to evaluate target images. The method of physiological experiments makes data acquisition more accurate, but the experimental process is complicated and places a psychological burden on the subjects, resulting in emotional fluctuations, which causes the evaluation data to deviate. Moreover, the complexity of the data prolongs the postprocessing cycle and increases the requirements for experimenters. At the same time, most existing evaluation methods consider only the differences in customer demand images, ignoring the correlation between images, which makes the results less objective.

The weight evaluation of a customer demand image is highly similar to the importance evaluation of nodes in complex networks. In complex networks, the network attributes of nodes are usually used as a key basis for evaluating the importance of nodes (Geng et al., 2019). Image adjectives and their relations can be regarded as nodes and edges, respectively, in the network. The weights of nodes can be obtained efficiently and accurately by evaluating attributes such as node degree, betweenness and closeness to the centre of the network. Moreover, the evaluation of the relationship between nodes is intuitive and simple, and it is more convincing as an evaluation method for customer demand images. This paper combines complex network theory and game theory to construct a customer demand image reasoning model. First, representative customer demand images are collected and screened, and an image word set is established. Then, a questionnaire is used to evaluate the associations between image words, and the association between image words is established according to the principle of maximum membership degree, forming a complex network between images. Then, the game theory model is used to comprehensively calculate the node degree attribute, the betweenness attribute and the closeness to the centre attribute of the complex network to obtain the weight ranking of the images. Finally, the image entropy algorithm is used to verify the results. Taking the evaluation of the customer demand image of a scooter as an example, the whole process is completed.

We organize the rest of the research as follows: Section 2 presents related research (including customer demand image evaluation, complex network theory, game theory and so on); Section 3 introduces the target image reasoning model construction process based on combining complex network theory and game theory; Section 4 presents the current experiment and results and verifies the results by using the image entropy algorithm; Section 5 discusses the entire process, the results and the significance of this paper; and finally, Section 6 concludes the paper and makes suggestions for future research.

2. Related Studies

2.1 Kansei images of products

In innovative design, customers' product preferences are the first issues designers need to consider (Hu et al., 2020). Cognitive psychology studies have shown that preference is the result of a high-level cognitive activity of human beings that reflects individuals' needs, preferences and interests, resulting in a comprehensive psychological image based on individuals' experiences and feelings (Luo et al., 2016). Analysing and processing customers' Kansei image information is an important step in optimizing product design schemes, which have an important impact on improving customer satisfaction and enterprise efficiency (Ni et al., 2019).

A Kansei image represents the feeling that people have towards products and is based on highly condensed and deep-seated human emotional activity (Luo et al., 2007). A product image represents the intuition associated with the user's product form through the senses of the user, and it fully conveys the emotional cognition of consumers (Zhou et al., 2018). In information processing, the product image mainly depends on the user's observation of a product and comparing that observation with personal experience, emotional states, and judgements (Yang et al., 2018). In an increasingly competitive market environment, efficiently and accurately identifying and meeting users' emotional needs is the key to enhancing product competitiveness, and the product form is the most direct way to reflect emotional factors. The design of product image forms has become an important point of competitiveness for enterprises (Park et al., 2015). Therefore, the product form design method based on Kansei images has become a research hotspot. In the product design process based on a Kansei image, the first step is to determine customer Kansei knowledge (Jiao et al., 2019) and form a customer Kansei image, which is usually expressed by adjectives. This requires applying comprehensive and quantitative visualization technology to customer preferences (Yamagishi et al., 2018). In recent years, with the proposal and development of Kansei engineering (KE) (Nagamachi, 1995), designers have come to understand consumers' preferences and complete innovative product designs by obtaining users' product image demands. This theory is currently the main method for designing innovative products based on customer demand (Li et al., 2018). The complexity and diversity of customers' Kansei images means that consumers have multidimensional perceptual needs for products. The ultimate goal of this paper is to efficiently and accurately determine the most important image demand, which is called the target image, from complex perceptual images.

The general process of obtaining a target image is shown in Fig. 1, and it includes four main steps: establishing a product sample set and image word set, establishing an image word evaluation system and samples, ranking the weights of the image words, and obtaining the target image. The evaluation data can be obtained by the explicit measurement method (EMM) and implicit measurement method (IMM) (Yang et al., 2018). The EMM determines customers' image cognition of products through psychological measurement, mainly using image scale evaluation (Chang et al., 2016). Data processing methods used with the EMM include the image entropy algorithm (Qiu et al., 2020) and cluster analysis (Huang et al., 2012). The IMM mainly determines image cognition indirectly through changes in physiological indicators (Hyun et al., 2017), and it can obtain data via EEG experiments and eye movement experiments; data processing is mainly carried out through third-party platforms. However, in the process of image scale evaluation, subjects need to provide a large amount of evaluation data, which easily causes cognitive overload and cognitive ambiguity, making the obtained data less objective and accurate. Although the data acquisition process in physiological experiments is objective, the experimental process is complicated, and subjects are prone to emotional fluctuations, which causes the evaluation data to deviate. Moreover, due to the complexity of the data and the long postprocessing cycle, the professional requirements of the experimenters are high. In this paper, complex network theory is used to improve the evaluation of the image scale. Through the evaluation of the correlation between image words, the cognitive load of subjects is reduced, and the correlation between image words is taken into account, which makes the image word evaluation process more efficient and the data more concise and accurate.

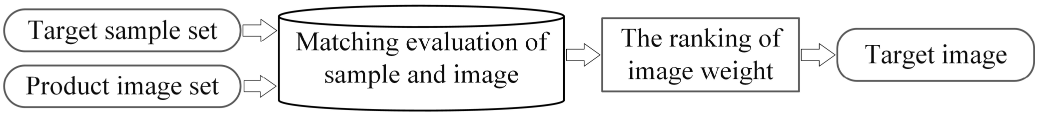

Fig. 1 Target image acquisition process

2.2 Complex networks

As an important research field in complexity science (Zhang et al., 2019), complex networks are mainly used to study the dynamic relationships among multiple objects using nodes and edges. Nodes represent the research objects, while edges represent the relationships between the nodes. The node degree, betweenness and closeness to the centre are three important attributes of complex networks. By using different node objects, complex networks can be used in many fields, such as sociology (Song et al., 2020), power grid modelling (Bose et al., 2020), and transportation and logistics decision-making (Bona et al., 2021).

In the field of product innovation, Lin et al. (2020) took patent keywords as complex network nodes and the co-occurrence relationships of various keywords in the same patent as the edges of the network to build a complex network of patent data and produce an innovative bathroom shower design. Xu et al. (2020) proposed a product gene network model based on the coding principles of isomorphism and isomerism. Through the comparative study of gene network data composed of product information in various environments, the cognitive differences between designers and customers on product images can be reduced to assist designers in accurately grasping customer needs from a macro perspective. Based on the multidimensional network analysis framework of complex networks, a design decision system

[DOI: 10.1299/jamdsm.2022jamdsm0062]

satisfying users' preferences was constructed (Wang et al., 2017). To improve the quality of innovative product design decision-making, Yang et al. (2019) integrated complex network theory into the product evaluation process and performed network analysis on the opinions of evaluators to help evaluators dynamically determine the importance of each round of evaluation; the analytic hierarchy process and used to quantitatively determine the weights of the evaluation indicators, making the design decision-making process more objective and accurate. Zhang et al. (2019) constructed a heterogeneous object (HEO) modelling method based on complex network theory with component units as nodes and the forced relationships between them as edges and verified the feasibility of this method with an example. Liu et al. (2020) constructed a data-driven concept network based on machine learning, which could inspire designers to create ideas by mining useful knowledge.

It can be seen from the above that complex network theory has been extensively and deeply studied in the innovative design of product modelling, and the results are outstanding. However, there is little research on determining customer demand, and in the product perceptual image design process, the first step is to determine the perceptual knowledge of customers (Jiao et al., 2019) to obtain the target image for product design. Therefore, this paper aims to apply complex network theory to the stage of acquiring target images in product design, taking the image words as the network nodes and the relationships between the words as the network edges. By evaluating the three network attributes of degree, betweenness and closeness to the centre for each image and introducing game theory to determine the weights of image words, the image evaluation results are made more efficient and objective.

2.3 Game theory

Game theory, a method derived from modern mathematics (Quan et al., 2019), is often used to study decision-making and the equilibrium results when decision-making subjects interact with each other (Lai et al., 2015), and it is an important method in multiattribute decision-making research (Sadeghi et al., 2011). By using various classification methods, game theory can be applied to finite games or infinite games, static games or dynamic games, and cooperative games or noncooperative games. The approach of game research depends on the problem-solving process adopted. Both players in a game take the other's decisions into consideration and aim to maximize their own interests. Game theory has been widely used in all aspects of life (Mu et al., 2020; Nazari et al., 2020; Rayati et al., 2020), especially for resource allocation (Mooselu et al., 2020; Sun et al., 2020) and risk assessment (Wang et al., 2021).

At the same time, game theory has developed rapidly in the field of product design. Geng et al. (2020) regarded the determination of the weight of customer demand as using a network game process and obtained the weight of customer demand by constructing a network game model of customer demand; however, nodes and edges were used in the network only to complete the processing of game theory data, and the attributes of the network itself were not studied. Chen et al. (2017) incorporated the fuzzy expression of quality into the process of quality function development and established a customer demand determination model based on game theory, which addressed the deficiency that the traditional customer demand determination method cannot consider multiple stakeholders. Jing et al. (2019) established a cooperative game model in the conceptual stage of product design, calculated the weight and influence utility of goals, and solved the conflict between economic indicators and technology in the design process.

The product design process is a complex system interaction process involving multiple agents and multiple decisions, especially in the evaluation stage of customer image demand. Based on the game theory method, this paper comprehensively evaluates and sorts the degree, betweenness and closeness to the centre of nodes in complex networks to obtain target images.

3. Method

The experimental process of this paper is established based on the qualitative and quantitative research methods shown in Fig. 2. This process includes establishing a sample set, acquiring an image set, constructing an image network, evaluating network attributes, evaluating image weights based on game theory, and verifying the results. First, sample pictures are collected in various ways, and a research sample set is established by morphological similarity evaluation. Second, through the network and other channels, the Kansei image words corresponding to the research cases are collected and screened, and the correlations between image words are obtained by a questionnaire survey. Then, the image network is established with the image words as the nodes and the relevance as the edges, and the network attributes are evaluated. Next, based on the equilibrium idea of game theory, the weight of each attribute of the network is obtained,

[DOI: 10.1299/jamdsm.2022jamdsm0062]

and each image is comprehensively evaluated and ranked. Finally, the image entropy algorithm is used to verify the accuracy of the results and discuss them.

3.1 Image evaluation of product form

First, the research products are determined, and the initial research samples and image words are obtained through market research and network collection. After screening, the research sample set S_i and image word set U_j are formed, where i=1,2,3, …, m; and j=1,2,3, …, n. Then, a questionnaire is used to evaluate the relationship between the images and words and obtain the correlations between images. Evaluations with strong correlations are given a score of 1, and evaluations with weak correlations or no correlation are given a score of 0.

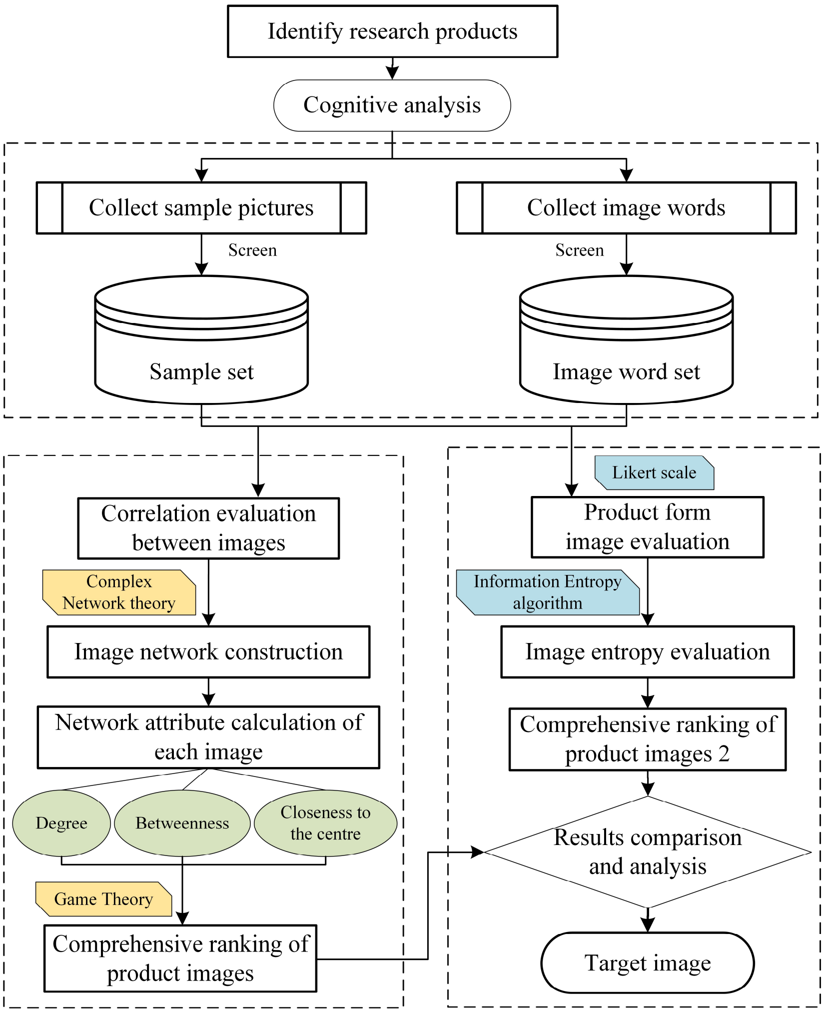

Fig. 2 Research flow chart

3.2 Research on image network attributes

According to the relevance evaluation results, a complex network is established between images. To ensure the rationality of the image network construction and attribute evaluation, based on Chen et al. (2017), this paper assumes the following:

(1) The correlations between image words are reasonable;

(2) The influence relationships between image words are symmetrical; that is, the influence of image A on image B is the same as that of image B on image A.

(3) The subjects who participate in the evaluation of the relationships between images are sufficiently familiar with the research objects, and they give their own reasonable opinions.

In the image network, the image words are used to construct the nodes, and the correlations between words are used to construct the edges. The network attributes of the nodes are usually used to evaluate the criteria of the importance of the nodes. Therefore, this paper studies three image word network attributes, namely, degree, betweenness and closeness

[DOI: 10.1299/jamdsm.2022jamdsm0062]

to the centre, and introduces game theory to comprehensively evaluate the image words.

Assuming that $D=\{d_1,d_2,\cdots,d_K\}$ is the set of all nodes in an undirected network, $|D|=K$, the attributes of the nodes (Geng et al., 2019) are as follows:

(1) Node degree (Friedkin., 2019)

As a basic parameter of network topology, the degree concerns the direct influence of a node in a static network, and it represents the ability of the node to establish a direct relationship with other nodes in the network. According to the local attributes of the network, the greater a node's degree value, the more directly the node is connected with other nodes, indicating that the node is more important in the network. When N_t is used to represent the number of other nodes directly connected with node d_t, N_t is defined as the degree of node d_t. If $N_t \le K-1$ holds in the network of K nodes, the attribute value of the node degree can be normalized to obtain:

$$C_\alpha(d_t)=\frac{N_t}{K-1} \tag{1}$$

In the product image network evaluation process, the greater the degree value of the image words is, the closer the correlation between the image and other images, and thus the greater its importance.

(2) Betweenness (Bian et al., 2017)

As a global variable, betweenness reflects the role and influence of a node, which indicates the influence of the node on the flow of information in the network. The higher the betweenness value of a node, the more influential the node is in the network. Taking node d_t as an example, define its betweenness as:

$$C_\beta(d_t)=\sum_{o\neq t\neq r}\frac{g_{or}(d_t)}{u_{or}} \tag{2}$$

where $g_{or}(d_t)$ represents the number of nodes d_t through which the shortest path between node d_o and node d_r passes and u_{or} indicates the shortest path number between node d_o and node d_r. For d_t, the normalized betweenness attribute value is:

$$C_{\overline{\beta}}(d_t)=\frac{2C_\beta(d_t)}{(K-1)(K-2)} \tag{3}$$

In the product image network evaluation process, the larger the betweenness value of an image is, the greater the influence of the image on other images and the more important the image is.

(3) Closeness to the centre (Yang et al., 2017)

The closeness to the centre reflects the proximity of a node to other nodes in the network. It is represented by the reciprocal of the sum of the distances from this node to other nodes. It is mainly used to measure the influence of this node on other nodes through the network. The closer a node is to the centre, the greater the compactness of the node; that is, the closer the node is to the centre of the network, the greater the importance of the node.

Taking node d_t as an example, l_{tq} is assumed to be the shortest distance from node d_t to node d_q in the network. If in a network of K nodes, the sum of the shortest distances from any node to all other nodes is $\sum_{q=1}^{K} l_{tq} \ge K-1$, then the normalized node closeness to the centre can be obtained as follows:

$$C_\theta(d_t)=\frac{K-1}{\sum_{q=1}^{K} l_{tq}} \tag{4}$$

The position of a node in the network reflects the importance of the image corresponding to the node in the evaluation of all images. The closer to the centre an image is, the greater the weight of the image in the evaluation.

3.3 Research on comprehensive image evaluation based on game theory

In Section 3.2, we described in detail the evaluation methods for the degree, betweenness and closeness to the centre of nodes in the network. However, in network evaluation, a single attribute cannot fully express the comprehensive evaluation results of nodes. To ensure the objective and accurate results of image evaluation, combined with the obvious advantages of game theory in balancing decision-making, this paper establishes a network attribute weight evaluation model based on game theory and achieves a comprehensive evaluation ranking of the image words. The attributes of node degree, betweenness and closeness to the centre are relevant, and the final comprehensive weight vector is a balanced decision. The specific steps are as follows:

Step 1: According to the calculated values of the degree, betweenness and closeness to the centre, the basic weight vector set $\lambda_j = \left\{\lambda_{j1}, \lambda_{j2}, \lambda_{j3}\right\}(j = 1, 2, \cdots, n)$ is obtained. We indicate any combination of n vectors as follows:

$$\lambda = \sum_{j=1}^{n} \omega_j \lambda_j^T \tag{5}$$

where $\omega_j > 0$, $\sum_{j=1}^{n} \lambda_j = 1$, λ is any possible weight vector in the weight set, and ω_j is the linear combination coefficient.

Step 2: The n linear combination coefficients ω_j are optimized by applying game theory to minimize the deviation between λ and each λ_j, as follows:

$$\min \left\| \sum_{j=1}^{n} \omega_j \lambda_j^T - \lambda_\delta \right\|_2 \quad (\delta = 1, 2, \cdots, n) \tag{6}$$

According to the differential properties of the matrix, Eq. (6) can be converted into:

$$\sum_{j=1}^{n} \omega_j \lambda_\delta \lambda_j^T = \lambda_\delta \lambda_\delta^T \quad (\delta = 1, 2, \cdots, n) \tag{7}$$

Converting this to a linear formula, we obtain Eq. (8) as follows:

$$\begin{bmatrix} \lambda_1\lambda_1^T & \lambda_1\lambda_2^T & \cdots & \lambda_1\lambda_n^T \\ \lambda_2\lambda_1^T & \lambda_2\lambda_2^T & \cdots & \lambda_2\lambda_n^T \\ \vdots & \vdots & \ddots & \vdots \\ \lambda_n\lambda_1^T & \lambda_n\lambda_2^T & \cdots & \lambda_n\lambda_n^T \end{bmatrix} \begin{bmatrix} \omega_1 \\ \omega_2 \\ \vdots \\ \omega_n \end{bmatrix} = \begin{bmatrix} \lambda_1\lambda_1^T \\ \lambda_2\lambda_2^T \\ \vdots \\ \lambda_n\lambda_n^T \end{bmatrix} \tag{8}$$

Step 3: $(\omega_1, \omega_2, \cdots \omega_n)$ is calculated through Eq. (8) and normalized to obtain the following:

$$\omega_j^* = \frac{\left|\omega_j\right|}{\sum_{j=1}^{n} \left|\omega_j\right|} \tag{9}$$

Therefore, the optimal weight vectors of the node degree, betweenness and closeness to the centre after comprehensive evaluation can be obtained as follows:

$$\lambda^* = \sum_{j=1}^{n} \omega_j^* \omega_j^T \tag{10}$$

According to λ^*, the comprehensive evaluation value of the j-th image can be calculated as follows:

$$W_j = \omega^*_{C_\alpha(d_t)} C_\alpha(d_t) + \omega^*_{C_{\bar{\beta}}(d_t)} C_{\bar{\beta}}(d_t) + \omega^*_{C_\theta(d_t)} C_\theta(d_t) \tag{11}$$

According to the size of W_j, all image words are evaluated and sorted to obtain the top ranked image as the target image.

3.4 Verification of the results based on image entropy

To verify the reliability of the results, the importance of image words is reordered based on the information entropy algorithm. Entropy is an important indicator in evaluating the stability of a system; it indicates the degree of chaos of the system, that is, the probability of the system being in a certain state, and it is a way of describing the relationships between the micro and macro states in a complex system (Lei et al., 2021). The greater the entropy value of a state is, the greater the probability that the system is in this state. Shannon (2001) first introduced the concept of information entropy to measure the uncertainty of information. As negative entropy is used to measure the amount of information, information entropy represents the degree of order of the system. In product design, Su et al. (2016) explored the differences in image cognition among users, designers and engineers in relation to product form, analysed the image cognition of product form by using information entropy, and proposed an evaluation method for product form image entropy based on comprehensive emotional needs. Yang et al. (2019) and Zhang et al. (2019) used the image entropy algorithm to calculate the amount of information of an image regarding product form and colour, respectively, to determine the image weight.

Based on the principle of information entropy, this paper calculates the image entropy of samples to obtain the weight and ranking of each image. The basic idea is to determine the weight of the image vocabulary based on the amount of information contained in the vocabulary. If the entropy value of certain image vocabulary is smaller, the amount of information it provides in the evaluation process is greater, and the greater its sensitivity is, the greater the weight it obtains. The less the sensitivity is, the smaller the weight obtained. The value of the product image represented by entropy is as follows:

$$\sigma_j = -\mu \sum_{i=1}^{m} (P_{ij} \ln P_{ij}) \tag{12}$$

where σ_j represents the entropy value of the image; i represents the sample set, i = 1, 2, 3..., m; j represents the image set, j = 1, 2, 3..., n; P_{ij} represents the probability of the j-th image of the i-th product sample, $0 \le P_{ij} \le 1$; μ is a constant; and $\mu = 1/\ln m$.

To ensure that the verification data were reliable, the Likert scale was used to obtain image evaluation data. The Likert scale is widely used to quantify the image perception of subjects, and it is generally divided into 5- or 7-point evaluations; the 5-point evaluation process is shown in Fig. 3.

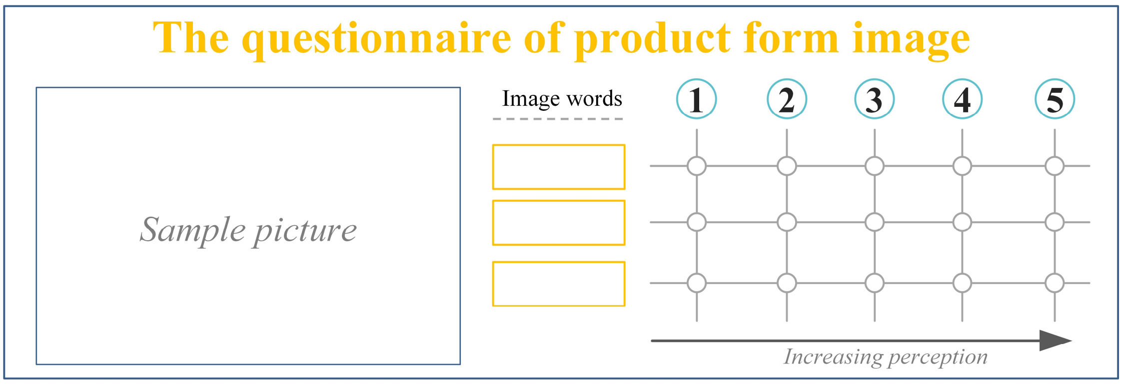

Fig. 3 5-point Likert scale evaluation method

[DOI: 10.1299/jamdsm.2022jamdsm0062]

In this paper, the five-level evaluation method was used to obtain the evaluation data of Kansei images, and the evaluation matrix was established as follows:

$$Y = \begin{bmatrix} Y_{11} & Y_{12} & \cdots & Y_{1n} \\ Y_{21} & Y_{22} & \cdots & Y_{2n} \\ \vdots & \vdots & Y_{ij} & \vdots \\ Y_{m1} & Y_{m2} & \cdots & Y_{mn} \end{bmatrix} \tag{13}$$

where Y_{ij} represents the average value of the evaluation of the j-th image of the i-th sample.

To reduce the error of the image evaluation results, the evaluation matrix Y was normalized to obtain the image decision matrix $\tilde{Y}$:

$$\tilde{Y} = \begin{bmatrix} \frac{Y_{11} - \min Y_{ij}}{\max Y_{ij} - \min Y_{ij}} & \frac{Y_{12} - \min Y_{ij}}{\max Y_{ij} - \min Y_{ij}} & \cdots & \frac{Y_{1n} - \min Y_{ij}}{\max Y_{ij} - \min Y_{ij}} \\ \frac{Y_{21} - \min Y_{ij}}{\max Y_{ij} - \min Y_{ij}} & \frac{Y_{22} - \min Y_{ij}}{\max Y_{ij} - \min Y_{ij}} & \cdots & \frac{Y_{2n} - \min Y_{ij}}{\max Y_{ij} - \min Y_{ij}} \\ \vdots & \vdots & \frac{Y_{ij} - \min Y_{ij}}{\max Y_{ij} - \min Y_{ij}} & \vdots \\ \frac{Y_{m1} - \min Y_{ij}}{\max Y_{ij} - \min Y_{ij}} & \frac{Y_{m2} - \min Y_{ij}}{\max Y_{ij} - \min Y_{ij}} & \cdots & \frac{Y_{mn} - \min Y_{ij}}{\max Y_{ij} - \min Y_{ij}} \end{bmatrix} \tag{14}$$

Then the probability of obtaining an image was as follows:

$$P_{ij} = y_{ij} \Big/ \sum_{i=1}^{m} y_{ij} \tag{15}$$

where y_{ij} represents the normalized data of the j-th image of the i-th sample.

Substituting the probability P_{ij} of each image into Eq. (12) to calculate the entropy value of the j-th image, the final weight of the image is:

$$\zeta_j = (1-\sigma_j) \Big/ \sum_{j=1}^{n} (1-\sigma_j) \tag{16}$$

According to the weight results, the images can be sorted again and compared with the results obtained by the method of this paper.

4. Case Study

Through market research, we used a scooter as an example to verify the research method. This method is also applicable to research on other products. In what follows, all the steps of the product form image evaluation process are discussed.

4.1 Determining the research sample and image words

A total of 64 sample pictures of scooters were collected from sales websites, physical stores, periodicals and other channels and included various brands on the market. A total of 8 research samples were obtained from the preliminary screening by an individual with a PhD in industrial design and product users based on form and brand. To prevent external factors such as brand and colour from influencing the results, the experimenter processed and numbered the samples to form a research sample set, as shown in Fig. 4.

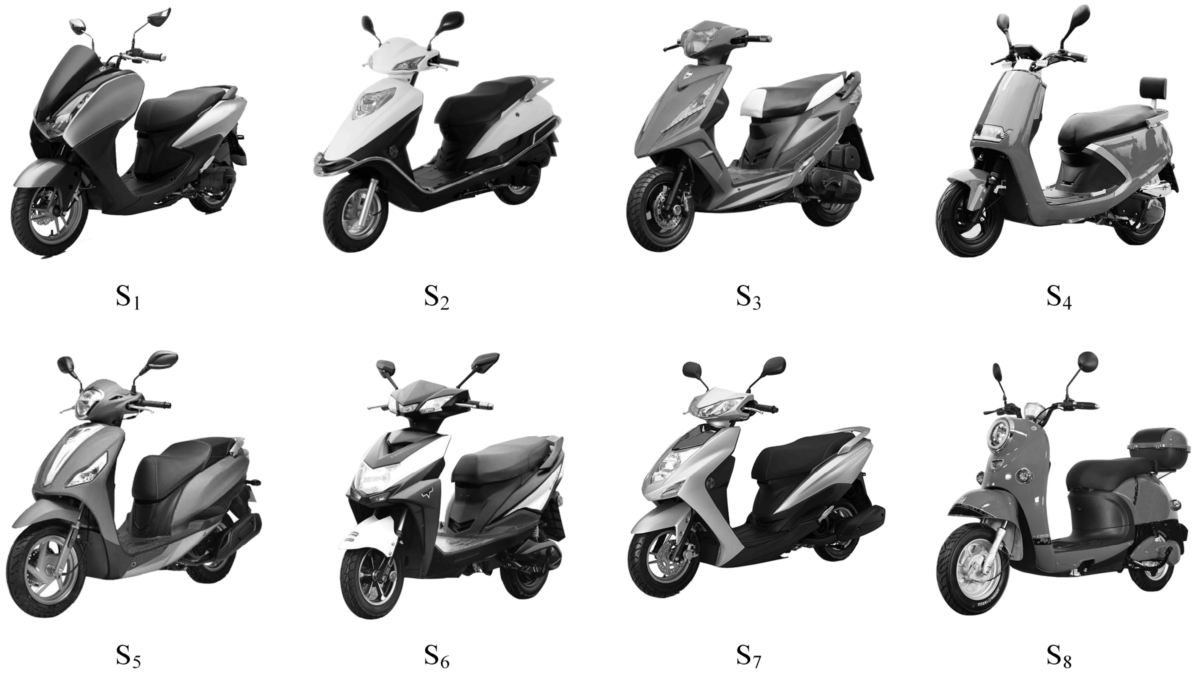

Fig. 4 Research sample set

According to the online and field survey of users' evaluations of the scooter, and referring to the product development plan of a scooter production company, some commonly used image words in the evaluation of motorcycle form were selected. Experts, including product development demand analysts, product development research department personnel, and graduate students with motorcycle design experience, were consulted to appropriately shrink and expand the set of image words and determine the final 12 image words used to form an image set, as shown in Table 1.

Table 1 Image word set

Number	**Image**	**Number**	**Image**	**Number**	**Image**
U_1	Technological	U_5	Atmospheric	U_9	Smart
U_2	Fashionable	U_6	Holistic	U_{10}	Fast
U_3	Strong	U_7	Useful	U_{11}	Individuality
U_4	Streamlined	U_8	Safe	U_{12}	Advanced

4.2 Evaluation of image relevance based on the network

In Accordance with the case, 4 users with experience in scooter use, 6 graduate students majoring in industrial design and 2 enterprise product designers were selected to form the test group to evaluate the correlation of product images. The 12 image vocabularies obtained were represented in a 12*12 evaluation form, which was evaluated by researchers and distributed to each participant after ensuring that the evaluation content was reasonable and credible. The participants were informed of the evaluation procedure: first, view 8 sample pictures, and then evaluate the correlations between pairs of image words. If there is a correlation between the words, a score of 1 should be given, and if no correlation or only a weak correlation exists, a score of 0 should be given. The final results were reviewed by the experimenter, and according to the principle of maximum membership, the data of all subjects were integrated to construct a complex network of image words. If the correlation evaluation was 1, an undirected edge was drawn between the two images, and if the evaluation was 0, no edge was drawn. The resulting image complex network is shown in Fig. 5.

[DOI: 10.1299/jamdsm.2022jamdsm0062]

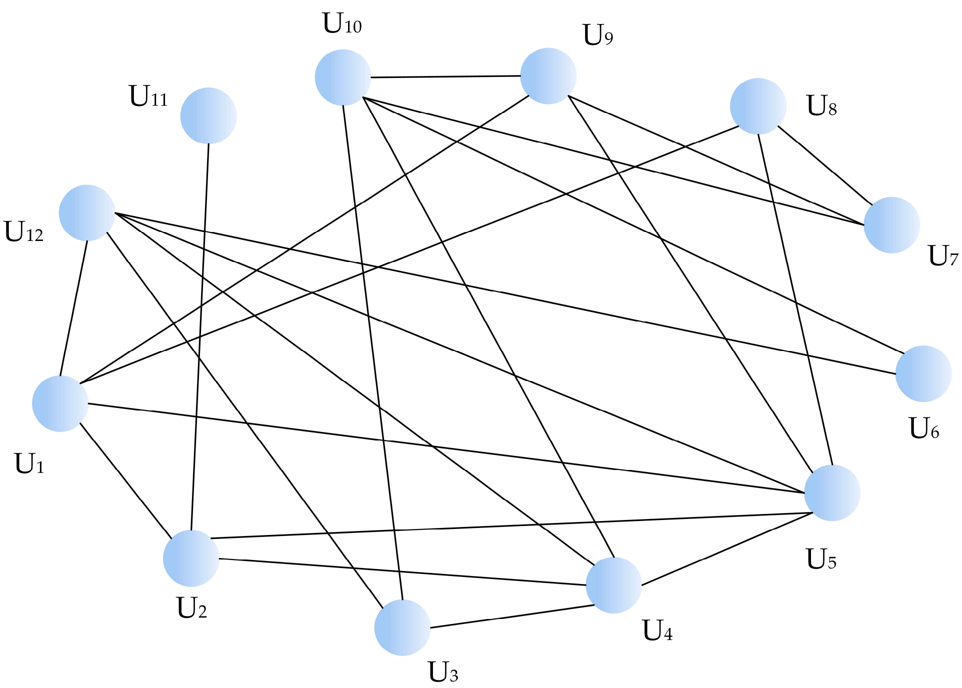

Fig. 5 Network diagram of the form image of a scooter

According to Fig. 5 and Eq. (1)-(4), the degree, betweenness and closeness to the centre were calculated for each image, and the results are shown in Table 2.

Table 2 Network attribute values of the scooter form images

Image	Degree	Betweenness	Closeness to the centre
U_1	0.455	0.096	0.647
U_2	0.455	0.170	0.611
U_3	0.273	0.011	0.524
U_4	0.455	0.092	0.647
U_5	0.545	0.119	0.733
U_6	0.182	0.009	0.500
U_7	0.273	0.036	0.500
U_8	0.273	0.010	0.500
U_9	0.364	0.054	0.579
U_{10}	0.455	0.131	0.611
U_{11}	0.091	0	0.393
U_{12}	0.545	0.133	0.647

4.3 Comprehensive evaluation of the image words based on game theory

Taking the three network attributes of the image words as the initial data for the comprehensive evaluation of the image, according to Eq. (5)-(10), the weights of the degree, betweenness and closeness to the centre were 0.34, 0.06 and 0.6, respectively. According to Eq. (11), the comprehensive evaluation value of each image was obtained as shown in Table 3.

Table 3 Comprehensive evaluation values of the scooter form images

Image	U_1	U_2	U_3	U_4	U_5	U_6
Evaluation value	0.4425	0.5315	0.4079	0.5484	0.6322	0.3624
Image	U_7	U_8	U_9	U_{10}	U_{11}	U_{12}
Evaluation value	0.3950	0.3934	0.4744	0.5292	0.2667	0.5815

[DOI: 10.1299/jamdsm.2022jamdsm0062]

According to the data in the table, the comprehensive evaluation order of the image words was: $U_5>U_{12}>U_4>U_2>U_{10}>U_9>U_1>U_3>U_7>U_8>U_6>U_{11}$. "Atmospheric" had the highest comprehensive evaluation value, so "Atmospheric" was chosen as the target image of the scooter form design.

4.4 Verification of the results based on image entropy

To increase the credibility of the image evaluation results and verify the feasibility of the evaluation method in combining complex network theory and game theory, this study used the image entropy algorithm to verify the results. The specific verification process is described in detail in Section 3.4.

In the verification process, we created a questionnaire using the Likert scale and obtained the initial data through a 5-point evaluation process. To ensure the objectivity of the data sources, we chose 12 subjects to evaluate the image relevance in this survey. Before the evaluation began, the purpose of this study and the rules for completing the questionnaire were fully explained to the participants, and the evaluation experiment was started after obtaining consent or confirmation. To ensure that the evaluation results were not affected by the order of the samples, we presented the samples in a random order in the questionnaire to obtain the most scientific and accurate evaluation results. The evaluation results were averaged and sorted, and the results are shown in Table 4.

Table 4 Image evaluation values of the product samples

	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8
U_1	3.500	2.083	3.333	3.250	3.250	3.083	2.167	2.917
U_2	3.333	1.833	3.083	4.083	2.917	2.500	1.833	4.333
U_3	4.000	2.667	3.333	3.333	3.333	3.250	2.917	3.333
U_4	3.000	2.500	2.917	2.583	3.500	2.833	2.833	2.417
U_5	2.750	2.583	3.250	3.083	3.083	2.750	2.583	2.917
U_6	3.167	3.417	3.417	3.833	3.417	2.417	3.000	3.500
U_7	3.167	2.750	3.583	2.250	2.833	3.167	2.250	2.083
U_8	3.583	2.333	3.083	2.417	3.333	3.167	2.583	2.167
U_9	3.333	2.583	2.417	2.333	2.917	3.000	2.667	2.583
U_{10}	2.750	3.583	3.167	2.750	3.583	3.583	3.250	3.000
U_{11}	3.750	2.583	3.333	3.750	3.083	3.083	2.167	3.833
U_{12}	4.000	1.917	2.750	3.583	3.250	2.917	1.917	3.417

Substituting the data in Table 4 into Eq. (12)-(16), the weight results of each image were calculated as shown in Fig. 6. According to the results in Fig. 6, the images were ranked as follows: $U_5>U_2>U_{10}>U_4>U_9>U_7>U_{12}>U_8>U_1>U_3>U_{11}>U_6$.

[DOI: 10.1299/jamdsm.2022jamdsm0062]

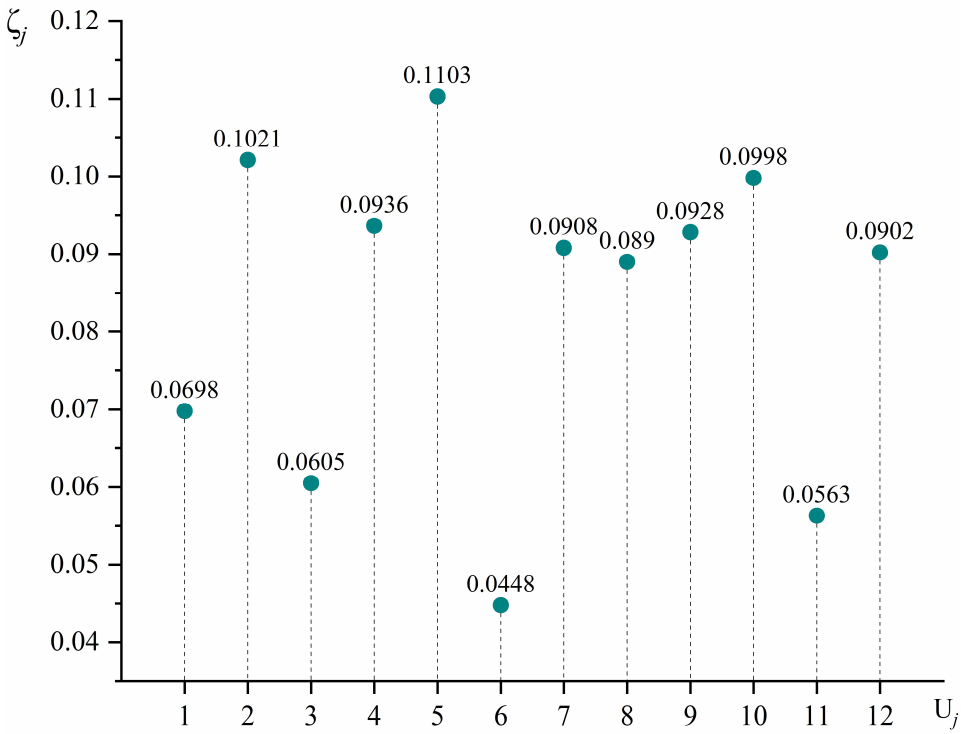

Fig. 6 Evaluation results of product image entropy

To make the comparison of results intuitive and concise, we normalized the experimental results and the results obtained in the verification process and then drew a comparison chart of the image evaluation results, as shown in Fig. 7.

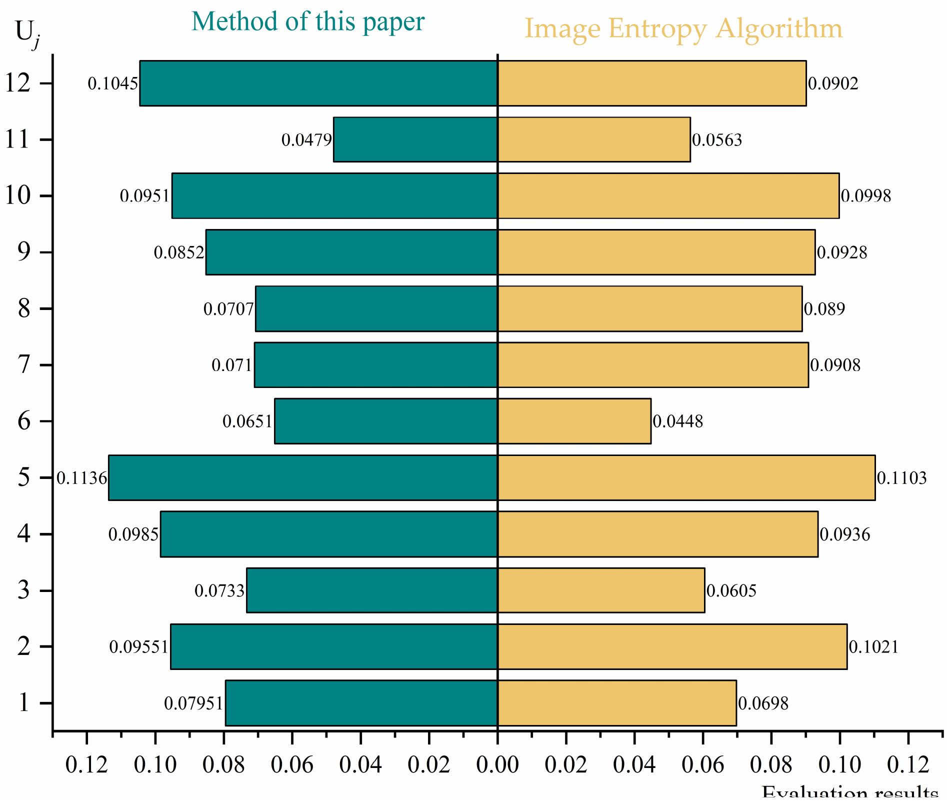

Fig. 7 Comparison of the image evaluation results

It can be seen from the comparison results in Fig. 7 that the overall trends of the results of the proposed method and those of the image entropy algorithm were relatively close: "Atmospheric" was ranked the highest, and "Holistic" and "Individuality" were ranked last. Similarly, the results for the images varied greatly. For example, U_{12} was ranked second, after "Atmospheric", by the proposed method, but the image entropy algorithm ranked U_{12} in the middle of the images. The image entropy algorithm ranked the "Fashionable" image second, but this image was ranked fourth by the proposed method. The reasons for the differences in the results are explained in the discussion section, but the results of the evaluation and acquisition of the target images for the product development process were consistent, which shows the reliability of the results of this paper.

5. Result Discussion

Currently, during product design, due to the lack of customer image information, designers often choose a product design target image based on their own experience rather than comprehensive customer image information (Yamagishi et al., 2018). The customer target image is not only the basis of product development but also the basis of marketing decisions (Ji et al., 2020). As target image acquisition provides the motive for and direction of product form optimization design, its accuracy is directly related to whether designers and enterprises can effectively design and develop products that meet customers' emotional needs (Yang et al., 2011). In this paper, we used complex network theory and game theory to obtain original data by evaluating the correlation between image words to comprehensively evaluate images and thus obtain the target image of a scooter as "Atmospheric". Compared with the results of the image entropy algorithm, the proposed method is intuitive and effective and improves evaluation efficiency. Compared with most current evaluation methods, the advantages of this method are as follows: (1) In the evaluation process, the participant sample comprised users, designers, and enterprise personnel, which allowed multiple stakeholders to be considered in the product development process, making the evaluation results more objective and accurate. (2) In the evaluation process, an image word relevance evaluation method was adopted, which helped ensure that the evaluation data were objective and accurate by considering the cognitive load of the subjects. (3) By calculating various network attributes based on complex network theory and game theory, the correlations between images were fully considered, which provided a basis for mutually evaluating the images.

By comparing the results of the two methods, the overall trend is found to be consistent, and both approaches rank " Atmospheric" the highest, which shows the reliability of the results. However, the methods also ranked some images differently. Through analysis, it can be seen that the difference in the evaluation results is caused by the different emphases of the two evaluation methods. The image entropy algorithm, as an objective weighting method, avoids subjectivity to a certain extent but considers only the internal relationships among the images, ignoring the correlations between them, which makes the evaluation result incomplete; the evaluation method based on complex network theory meets this demand to a certain extent. In a follow-up study, we will consider a target image evaluation method that combines these two methods, using the method proposed in this paper to evaluate between images and the image entropy algorithm to evaluate within images, and then comprehensively evaluate the results of the two methods through the idea of a cooperative game as a more comprehensive and accurate method of obtaining target images.

6. Conclusions and Further Research

Because of the importance of target images in product design and development, it is necessary to use images when evaluating potential new designs. In this paper, we aimed to develop an efficient and accurate method for mining customer preferences to obtain product target images. Therefore, we proposed a calculation model combining complex network theory with game theory. First, after extensive investigation and screening, the product sample set and image word set were determined, and the initial data were obtained by having various stakeholders evaluate the correlations between images. Then, based on complex network theory, an image network was constructed, and the node degree, betweenness, and closeness to the centre were calculated. Then, based on the game theory model, the weights of the three network attributes were calculated to obtain a comprehensive evaluation value for each image. Finally, the image entropy algorithm was used to verify the results. Although this paper used a scooter, the method developed here can also be used to obtain and evaluate target images for other products.

Next, our future research will expand on the current work in two ways. (1) To explore more comprehensive and accurate target image acquisition methods, the method proposed in this paper will be combined with the image entropy algorithm to obtain evaluation rankings of images based on different dimensions, and then the target images will be obtained by integrating the weights of the two methods using game theory to make the evaluation results more objective and accurate. (2) According to the results of this paper, the design elements of the target product will be evaluated by combining complex network theory and game theory, and the importance order of the design elements in the product image modelling design process will be obtained to clarify the modelling design direction.

Acknowledgement

This research is supported by National Natural Science Foundation of China (51705226).

References

Bian, T., Hu, J., and Deng, Y., Identifying influential nodes in complex networks based on AHP, Physica A Statistical Mechanics & Its Applications, Vol.479, No4 (2017), pp.422-436.

Bona, A., Rosa, M., Fonseca, K., and Lüders, R., A reduced model for complex network analysis of public transportation systems, Physica A, Vol.567 (2021), DOI: 10.1016/j.physa.2020.125715

Bose, D., Chanda, C., and Chakrabarti, A., Vulnerability assessment of a power transmission network employing complex network theory in a resilience framework, Microsystem Technologies, Vol.26 (2020), pp.2443-2451.

Chang, Y., Chen, C., Kansei assessment of the constituent elements and the overall interrelations in car steering wheel design, International Journal of Industrial Ergonomics, Vol.56 (2016), pp.97-105.

Chen, Y., and Yu, Q., A Game Theory-based Approach to Determining the Weights of Customer Requirements, Journal of Systems & Management, Vol.26, No.1 (2017), pp.196-199 (in Chinese).

Friedkin, N., Theoretical foundations for centrality measures, American Journal of Sociology, Vol.96, No.6 (1991), pp. 1478-1504.

Geng, X., and Bo, Z., Approach to determine customer requirements weights weight based on network game, Computer Integrated Manufacturing Systems, Vol.26, No.10 (2020), pp.2792-2798 (in Chinese).

Geng, X., and Wang, J., Evaluation of product service system design based on complex network and PROMETHEEⅡ, Computer Integrated Manufacturing Systems, Vol.25, No.9 (2019), pp.2324-2333 (in Chinese).

Guo, Z., Lin, L., and Yang, M., Product image extraction model construction based on multi-modal implicit measurement of unconsciousness, Computer Integrated Manufacturing Systems (in Chinese). https://kns.cnki.net/kcms/detail/11.5946.TP.20201026.0949.004.html.

Hu, J., Chen, B., Source, Operating Mechanism, and Evaluation of Innovative Design, Packaging Engineering, Vol.41, No.18 (2020), pp.60-70 (in Chinese).

Huang, Y., Chen, C., and Khoo, L., Kansei clustering for emotional design using a combined design structure matrix, International Journal of Industrial Ergonomics, Vol.42 (2012), pp.416-427.

Hyun, K., Lee, J., and Kim, M., The gap between design intent and user response: identifying typical and novel car design elements among car brands for evaluating visual significance, Journal of Intelligent Manufacturing, Vol.28 (2017), pp.1729-1741.

Ji, X., Gao, Q., Li, X., and Gao, F., Reviews mining and requirements elicitation methodology considering product attributes' hierarchy, Computer Integrated Manufacturing Systems, Vol.26, No.3 (2020), pp.747-759 (in Chinese).

Jiang, S., Jing, L., Peng, X., Chai, H., and Li, J., Conceptual design conceptual scheme optimization based on integrated design objectives, Concurrent Engineering: Research and Applications, Vol.26, No.3 (2018), pp.231-250.

Jiao, Y., and Qu, Q., A proposal for Kansei knowledge extraction method based on natural language processing technology and online product reviews, Computers in Industry, Vol.108 (2019), pp.1-11.

Jing, L., Li, Z., Peng, X., Li, J., and Jiang, S., A relative equilibrium decision approach for concept design through fuzzy cooperative game theory, Journal of Computing and Information Science in Engineering, Vol.19, No.4 (2019), pp.1-24.

Kin, W., Ko, T., Rhiu, I., and Yun, M., Mining affective experience for a kansei design study on a recliner, Applied Ergonomics, Vol.74 (2019), pp.145-153.

Lai, C., Chen, X., Chen, X., Wang, Z., Wu, X., and Zhao, S., A fuzzy comprehensive evaluation model for flood risk based on the combination weight of game theory, Natural Hazards, Vol.77, No.2 (2015), pp.1243-1259.

Lei, Q., Lee, J., Huang, X., and Kawasaki, S., Entropy-based classification of elementary cellular automata under asynchronous updating: An experimental study, Entropy, Vol.23 (2021), pp.1-18.

Li, F., Li, W., and Li, Y., Weight calculation and transformation method of customer requirements based on double layer association[J]. Computer Integrated Manufacturing Systems, Vol.24, No.11 (2018), pp.2836-2845 (in Chinese).

Lin, L., Zhang, Y., Niu, Y., and Yang, M., Unbiased design method for product kansei image design based on network evaluation data, Journal of Southeast University (Natural Science Edition), Vol.50, No.1 (2020), pp.26-32 (in Chinese).

Lin, W., Lai, R., and Xiao, R., Patent data-driven product innovative design based on complex network, China Mechanical Engineering, Vol.31, No.7 (2020), pp.842-852 (in Chinese).

Liu, Q., Wang, K., Li, Y., and Liu, Y., Data-driven concept network for inspiring designers' idea generation, Journal of Computing and Information Science in Engineering, Vol.20, No.3 (2020), pp.1-39.

Luo, S., and Pan, Y., Research progress of Kansei image theory, technology and application in product design, Journal of Mechanical Engineering, Vol.43, No.3 (2007), pp.8-12 (in Chinese).

Luo, S., Li, W., and Fu, Y., Consumer preference-driven SUV product family profile gene design, Journal of Mechanical Engineering, Vol.52, No.2 (2016), pp.173-181 (in Chinese).

Maleki, S., Aghdaie, S., Shahin, A., and Ansari, A., Investigating the relationship among the Kansei-based design of chocolate packaging, consumer perception, and illingness to buy, Journal of Marketing Communications, (2019), DOI: 10.1080/13527266.2019.1590855.

Moon, H., Park, J., and Kim, S., The importance of an innovative product design on customer behavior: Development and validation of a scale, Journal of Product Innovation Management, Vol.32, No.2 (2015), pp.224-232.

Mooselu, M., Nikoo, M., Latifi, M., Sadegh, M. Wardy, M., and Rawas, G., A multi-objective optimal allocation of treated wastewater in urban areas using leader-follower game, Journal of Cleaner Production, Vol.267 (2020), DOI: 10.1016/j.jclepro.2020.122189

Mu, C., Wang, K., Ni, Z., and Sun, C., Cooperative differential game-based optimal control and its application to power systems, IEEE Transactions on Industrial Informatics, Vol.16, No.8 (2020), pp.5169-5179.

Nagamachi, M., Kansei Engineering: A new ergonomic consumer-oriented technology for product development, International Journal of Industrial Ergonomics, Vol.15 (1995), pp.3-11.

Nazari, S., Ahmadi, A., Rad, S., Ebrahimi, B., Application of non-cooperative dynamic game theory for groundwater conflict resolution, Journal of Environmental Management, Vol.270 (2020), pp.1-11.

Ni, J., Wang, Z., Lian, X., and Zhou, J., Optimization method of product design schemes based on preference information, Computer Integrated Manufacturing Systems, Vol.25, No.5 (2019), pp.1238-1247 (in Chinese).

Park, J., Gunn, F., Lee, Y., and Shim, S., Consumer acceptance of a revolutionary technology-driven product: The role of adoption in the industrial design development, Journal of Retailing and Consumer Services, Vol.26 (2015), pp.115-124.

Qiu, K., Su, J., Zhang, X., and Yang, W., Evaluation and balance of cognitive friction: Evaluation of product target image form combining entropy and game theory, Symmetry, Vol.12 (2020), pp.1-19.

Quan, H., Li, S., Wei, H., and Hu, J., Personalized product evaluation based on GRA-TOPSIS and Kansei engineering, Symmetry, Vol.11, No.7 (2019), pp.1-21.

Rayati, M., Bozorg, M., Ranjbar, A., and Cherkaoui, R., Balancing management of strategic aggregators using non-cooperative game theory, Electric Power Systems Research, Vol.184 (2020), pp.1-12.

Sadeghi, A., and Zandieh, M., A game theory-based model for product portfolio management in a competitive market, Expert Systems with Applications, Vol.38, No.7 (2011), pp.7919-7923.

Shannon, C., A mathematical theory of communication, Mobile Computing and Communications Review, Vol.5, No.1 (2001), pp.3-55.

Song, X., Jiang, W., Liu, X., Lu, H., Tian, Z., and Du, X., A survey of game theory as applied to social networks, Tsinghua Science & Technology, Vol.25, No.6 (2020), pp.734-742.

Su, J., Zhang, X., Jing, N., and Chen, X., Research on the entropy evaluation of product styling image under the cognitive difference, Journal of Mechanical Design, Vol.33, No.3 (2016), pp.105-108 (in Chinese).

Sun, Q., Yang, G., Wang, X., and Chen, Y., Cooperative game-oriented optimal design in constraint -following control of mechanical systems, Nonlinear Dynamics, Vol.7 (2020), pp.1-19.

Wang, M., Chen, W., Huang, Y., Contractor, N., and Fu, Y., Modeling customer preferences using multidimensional network analysis in engineering design, Design Science, Vol.2, No.11 (2017), pp.1-28.

Wang, Z., Li, C., and Jin, X., Evolutionary dynamics of the interdependent security games on complex network, Applied

Mathematics and Computation, DOI: 10.1016/j.amc.2021.126051
Wang, Z., Liu, W., Yang, M., and Han, D., Product form image design based on elliptic Fourier, Computer Integrated Manufacturing Systems, Vol.26, No.2 (2020), pp.481-495 (in Chinese).
Wu, R., Jiang, P., Lu, P., and Zhang, Y., Research on demand transformation process based on QFD in product design, Computer Integrated Manufacturing Systems, http://kns.cnki.net/kcms/detail/11.5946.tp.20191104.1140.012.html (in Chinese).
Xie, J., Bi, Y., Sha, Z., Wang, M., Fu, Y., Contractor, N., Gong, L., and Chen, W., Data-Driven Dynamic Network Modeling for Analyzing the Evolution of Product Competitions, Journal of Mechanical Design, Vol.142, No.3 (2020), pp.1-14.
Xu, B., Zhu, Y., Liu, X., Lu, C., and Chen, F., Comparison of product image gene network between designers and users, Packaging Engineering, Vol.41, No.8 (2020), pp.112-119 (in Chinese).
Yamagishi, K., Seki, K., and Nishimura, H., Requirement analysis considering uncertain customer preference for Kansei quality of product, Journal of Advanced Mechanical Design, Systems, and Manufacturing, Vol.12, No.1 (2018), pp.1-13.
Yang, C., A classification-based Kansei engineering system for modeling consumers' affective responses and analyzing product form features, Expert Systems with Applications, Vol.38 (2011), pp.11382-11393.
Yang, C., Chen, C., and Tang, Z., Study of electroencephalography cognitive model of product image, Journal of Mechanical Engineering, Vol.54, No.23 (2018), pp.126-136 (in Chinese).
Yang, M., Lin, L., and Milekic, S., Affective image classification based on user eye movement and EEG experience information, Interacting with Computers, Vol.30, No.5 (2018), pp.417-432.
Yang, W., Su, J., Qiu, K., Zhang, X., and Zhang, S., Research on evaluation of product image design elements based on eye movement signal, Proceedings of the 21st HCI International Conference (2019), pp.214-226.
Yang, Y., Gang, X., Mining important nodes in directed weighted complex networks, Discrete Dynamics in Nature and Society, Vol.97, No5 (2017), pp.1-7.
Yang, Y., Tian, H., and Jiao, S., Product Design Evaluation Method Using Consensus Measurement, Network Analysis, and AHP, Mathematical Problems in Engineering, DOI: 10.1155/2019/4042024
Yao, G., Xue, C., Wang, H., and Yan, B., Design method for coach styling design based on image cognition, Journal of Southeast University (Natural Science Edition), Vol.46, No.6 (2016), pp.1198-1203 (in Chinese).
Yeh, Y., Prediction of Optimized Color Design for Sports Shoes Using an Artificial Neural Network and Genetic Algorithm, Applied Sciences, Vol.10 (2020), pp.1-19.
Zhang, D., Zhao, Z., Zhou, Y., and Guo, Y., A novel complex network-based modeling method for heterogeneous product design, Cluster Computing, Vol.22 (2019), pp.7861-7872.
Zhang, H., and Yao, Y., An integrative vulnerability evaluation model to urban road complex network, Wireless Personal Communications, Vol.107 (2019), pp.193-204.
Zhang, X., and Yang, M., Color image knowledge model construction based on ontology, Color Research and Application, Vol.44 (2019), pp.651-662.
Zhou, A., Su, J., Yan, S., Ouyang, J., and Zhang, S., Product multi-image prediction model based on aesthetic measure of form, Journal of Graphics, Vol.39, No.4 (2018), pp.654-660 (in Chinese).

ISSN 1008-973X
CODEN ZDXGFS

JOURNAL OF ZHEJIANG UNIVERSITY
ENGINEERING SCIENCE

浙江大学学报

工学版

ISSN 1008-973X

12/2022

第 56 卷 第 12 期 Vol.56 No.12

中国·杭州 HANGZHOU CHINA

ZHEJIANG DAXUE XUEBAO (GONGXUE BAN)

浙江大学学报(工学版)

第 56 卷第 12 期　　2022 年 12 月

目　次

·机械工程·

·计算机技术·

第 56 卷第 12 期
2022 年 12 月

浙 江 大 学 学 报（工学版）
Journal of Zhejiang University (Engineering Science)

Vol.56 No.12
Dec. 2022

DOI: 10.3785/j.issn.1008-973X.2022.12.005

面向多域协同的复杂产品再设计模块主从识别

邱凯[1]，苏建宁[2]，张书涛[2]，张志鹏[1]，刘世锋[1]
(1. 兰州理工大学 机电工程学院，甘肃 兰州 730050；2. 兰州理工大学 设计艺术学院，甘肃 兰州 730050)

摘 要：为了在多主体参与、多需求共存条件下有效识别复杂产品再设计中各模块的主从关系，提升再设计效能，构建包括认知域、需求域及模块域的多域协同评价方法. 基于认知域中不同认知主体的情感需求及物理需求，完成设计需求域的建立. 结合模糊评价及相对偏好分析，获取需求域映射的各模块域间映射重要度. 考虑模块间的关联关系，提出模糊设计结构矩阵理论与 DEMATEL 结合，获取各模块的域内相关重要度. 运用合作博弈思维建立结合域间映射重要度及域内相关重要度的综合评价模型，识别各模块的主从关系. 相较于从单一角度进行模块重要度分析模式，所提方法的评价结果更为客观、全面、准确. 以 CKA6180 数控机床为例，验证多域协同的模块主从关系评价方法的有效性与可行性.

关键词：复杂产品再设计；多域协同；产品模块；主从识别；综合评价模型
中图分类号：TB 472　　**文献标志码**：A　　**文章编号**：1008−973X（2022）12−2358−09

Leader-follower identification of complex product redesign modules for multi-domain collaboration

QIU Kai[1], SU Jian-ning[2], ZHANG Shu-tao[2], ZHANG Zhi-peng[1], LIU Shi-feng[1]
(1. *School of Mechanical and Electronical Engineering*, *Lanzhou University of Technology*, *Lanzhou* 730050, *China*;
2. *School of Design Art*, *Lanzhou University of Technology*, *Lanzhou*, 730050, *China*)

Abstract: A multi-domain collaborative evaluation method including cognitive domain, demand domain and module domain was constructed, in order to effectively identify the master-slave relationship of each module in complex product redesign under the condition of multi-agent participation and multi-demand coexistence, and to improve the efficiency of redesign. The design requirements domain was established based on the emotional and physical needs of different cognitive subjects in the cognitive domain. Combined with the fuzzy evaluation and the relative preference analysis, the inter-domain mapping importance of each module for the requirement domain mapping was obtained. Considered the connection relationship among modules, a fuzzy design structure matrix combined with DEMATEL was proposed to obtain the intra-domain correlation importance of each module. Using the cooperative game method, a comprehensive evaluation model was established, which combined the inter-domain mapping importance and the intra-domain correlation importance to identify the master-slave relationship of each module. Compared with the module importance analysis mode from a single perspective, the method obtained more objective, comprehensive and accurate evaluation results. Taking the CKA6180 CNC machine tool as an example, the effectiveness and feasibility of the multi-domain collaborative evaluation method were verified.

Key words: complex product redesign; multi-domain collaboration; product module; leader-follower identification; comprehensive evaluation model

收稿日期：2021−12−31.　　**网址**：www.zjujournals.com/eng/article/2022/1008-973X/202212005.shtml

基金项目：国家自然科学基金资助项目（52165033）；甘肃省自然科学基金资助项目（20JR10RA168）；甘肃省教育厅优秀研究生“创新之星”资助项目（2021CXZX-445）.

作者简介：邱凯（1992—），男，博士生，从事产品创新设计研究. orcid.org/0000-0003-2071-4425. E-mail：Qiukai@email.cn
通信联系人：苏建宁，男，教授. orcid.org/0000-0002-2409-9207. E-mail: sujn@lut.edu.cn

面临激烈的市场竞争，以绿色、创新及差异化为目标的复杂产品已成为机械装备制造企业及学术研究领域关注的重点[1-2]，但开发成本高、更新换代周期长的特征[3]与经济全球化进程的加快、不同认知主体需求[4]的持续变化存在突出矛盾. 对在役时期的复杂产品进行再设计，是满足市场需求、提升品牌价值的必要途径，也是完善产品绿色性能的重要策略. 受到资源、环境与经济等的约束，企业无法对产品的所有模块同时进行再设计[5]，一般是通过替换或改进部分模块实现整体的再设计过程. 因此，对关键模块的识别是该过程的重要基础[6]，也是显著提高复杂产品系统质量及可靠性的重要途径之一[7].

产品模块主从关系的研究包括关键设计参数[8]、关键设计部件[9]、关键功能需求[10]等的确定. 赖荣燊等[5]构建功能模块的绿色性能评价指标体系，运用模糊层次分析及灰色关联分析，研究了功能模块再设计的优先次序识别. 褚学宁等[11]通过建立关键功能模块的性能监测参数到设计参数的映射关系，实现了用于产品开发或更新换代的关键设计参数识别. 张付英等[12]将可持续用户需求转换为产品的技术特性及功能模块，并识别影响产品可持续性的关键功能模块，为产品后续再设计提供了新的方向. 上述规划设计研究致力于产品关键模块的识别. 随着市场需求的不断变化，功能需求[13-14]不再是产品升级改造的唯一考虑因素，对于不同认知主体在情感[15]、品牌[16]、色彩[17]、美度[18]等的需求分析使得产品再设计的过程呈现多主体参与[19]、多需求共存[20]的显著特征. 现阶段针对模块主从识别的研究存在以下问题：1）需求获取着重考虑以功能、结构为主的物理需求，对不同认知主体产生的差异化情感需求分析不足；2）未考虑功能模块的关联关系造成模块重要性评估信息流失，使评价结果不全面.

本研究从不同认知主体情感需求结合物理需求角度考虑，构建复杂产品再设计的认知域及需求域，将设计模块的关联关系纳入评价过程，结合博弈论建立综合评价模型，修正再设计过程中模块主从关系评价结果. 通过认知主体-设计需求-功能模块的多域映射及协同效应提升复杂产品再设计效能，指导后续产品系列化的创新设计.

1　构建多域系统

如图 1 所示，复杂产品再设计是多认知主体参与、多领域协同的系统工程，设计需求变更是主要驱动力；多认知主体需求挖掘、评价是产品再设计的关键. 需求驱动的设计是由需求-功能-结构的映射过程[21]；完善多认知主体域-设计需求域-模块域的映射与模块域中各模块的关联关系评价是复杂产品再设计的关键步骤.

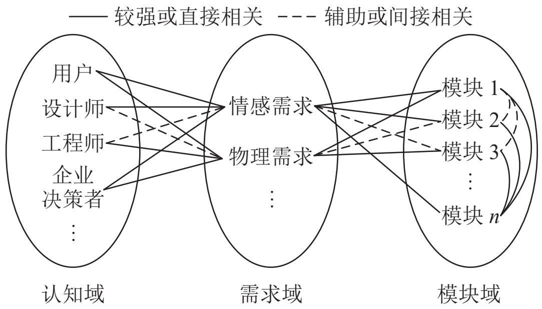

图 1　复杂产品的多域映射

Fig.1　Multi-domain mapping of complex product

1.1　构建认知域

复杂产品的再设计是将量化后“人”的需求向产品属性有效映射的过程. 随着复杂产品形态、功能及结构等的高度集成，传统的“人”的角色发生重大变化，呈现出多主体参与的主要特征：“人”不再仅是指用户 M，还包括设计师 G、工程师 E、企业决策者 U 等，并出现群智设计[22]概念. 由于不同认知主体的认知模式与专业背景存在一定差异，造成在感知、需求表达、方案决策等方面的需求不同，如用户与设计师之间[23]，设计师、用户、工程师三者之间[19]. 针对复杂产品建立完整的认知主体域是挖掘、综合评价设计需求的重要前提. 认知域 C 表示为

$$C = \{M, G, U, E, \cdots, X\}. \tag{1}$$

式中：X 表示某类认知主体. 通过分类研究完成不同认知主体的需求挖掘与评价，形成从认知域到需求域的映射.

1.2　构建需求域

设计需求域一般包括情感需求和物理需求. 情感需求是同类产品实现差异化的主要来源，主要体现在产品的外在表现形式，可以通过感性形容词进行表达（如形容数控机床的感性词语：大气的、稳重的）. 物理需求须保证产品在物理层面上满足认知主体需求，主要强调产品的功能，如加工精度高、操作便捷. 设计需求域 R 表示为

$$\left.\begin{aligned} &R = \{R_{\mathrm{K}}, R_{\mathrm{F}}\}; \\ &R_{\mathrm{K}} = (O_{\mathrm{K}}, Q_{\mathrm{K}}),\ R_{\mathrm{F}} = (O_{\mathrm{F}}, Q_{\mathrm{F}}). \end{aligned}\right\} \tag{2}$$

式中：R_{K} 为情感需求，R_{F} 为物理需求，Q_{K}、Q_{F} 分

别为情感需求及物理需求的获取方法，O_{K}、O_{F} 分别为情感需求及物理需求的评价方法.

1.3 构建模块域

复杂产品的模块域主要由各功能模块组成.根据功能间的相关性，企业常以功能模块为对象进行现役产品的升级或再设计，设计师团队通过功能模块的主从评估确定产品升级或再设计的模块优先次序.设计需求与功能是紧密相关的，需求域与模块域 S 相互映射，即

$$\left.\begin{array}{l} S=\{S_1,S_2,\cdots,S_t,\cdots,S_{t^*}\}; \\ R_t \to S_t,\ S_{\mathrm{S}}=S_{\mathrm{V}}(S). \end{array}\right\} \tag{3}$$

式中：S_t 为域中的第 t 个功能模块，与设计需求 R_t 对应，$t=1,2,3,\cdots,t^*$；S_{V} 为功能模块相关关系的评价方法；S_{S} 为评价结果.

2 多域协同的功能模块重要度评估

2.1 基于熵的目标情感需求获取

情感需求表征着认知主体对产品的整体评价.研究者常采用口语分析、意象尺度评价获取目标情感需求.熵[24]作为衡量系统稳定性的重要指标，用于挖掘目标情感需求.初始情感需求意象熵值 $\tilde{\sigma}_j$ 表示为

$$\tilde{\sigma}_j=-c\sum_{i=1}^{m} I_{ij}\ln I_{ij};\quad j=1,2,\cdots,n. \tag{4}$$

式中：I_{ij} 为第 i 个样本第 j 项初始情感需求的概率，$0 \leqslant I_{ij} \leqslant 1.0$；$c$ 为常数，$c=1/\ln m$.

采用五级李克特量表量化认知主体的情感需求并建立评价矩阵为

$$\tilde{\boldsymbol{D}}=\begin{bmatrix} \tilde{D}_{11} & \tilde{D}_{12} & \cdots & \tilde{D}_{1n} \\ \tilde{D}_{21} & \tilde{D}_{22} & \cdots & \tilde{D}_{2n} \\ \vdots & \vdots & & \vdots \\ \tilde{D}_{m1} & \tilde{D}_{m2} & \cdots & \tilde{D}_{mn} \end{bmatrix}. \tag{5}$$

式中：$\tilde{D}_{ij}$ 为第 i 个样本第 j 项情感需求的认知主体评价均值.为了减少评价过程中的误差，对评价矩阵 $\tilde{\boldsymbol{D}}$ 进行归一化处理，得到情感需求决策矩阵 $\hat{\boldsymbol{D}}$，从而获得各情感需求的概率为

$$I_{ij}=y_{ij}\Big/\sum_{j=1}^{n} y_{ij}. \tag{6}$$

式中：y_{ij} 为第 i 个样本第 j 项情感需求的归一化数值.由式(4)计算得到第 j 个情感需求的熵值 $\tilde{\sigma}_j$，该情感需求在整个评价过程中的权重为

$$\omega_j=(1-\tilde{\sigma}_j)\Big/\sum_{j=1}^{n}(1-\tilde{\sigma}_j). \tag{7}$$

根据各情感需求的权重值，选取权重排序靠前的为该类认知主体的目标情感需求 R'_{K}.同理，可以得到其他类别认知主体的目标情感需求，以此获得本研究的情感需求 R_{K}.

2.2 物理需求获取

物理需求作为产品基本功能的体现，是不同产品间差异的主要来源.通过对该产品认知主体的访谈和调研，获取主体的初始物理需求集为

$$R'_{\mathrm{F}}=\left\{H_1^p,H_2^p,\cdots,H_k^p\right\}. \tag{8}$$

式中：H_k^p 为第 p 个访谈对象的第 k 项物理需求，且 $p\in\mathbf{N}^*,k\in\mathbf{N}^*$.同理，可以得到其他类别认知主体的物理需求.采用语义评价术语对 R'_{F} 进行逐一评价并转换，得到最终的 R_{F}.由此，完成设计需求域 R 的构建.

2.3 基于相对偏好关系的功能模块映射重要度评估

假设 R 中包含 R_α，且 $1\leqslant\alpha\leqslant\alpha^*$，由该产品领域专家 $P_\chi(1\leqslant\chi\leqslant\chi^*)$ 基于公理化设计[25]思想进行需求及需求与功能模块间的映射关系评价.由于评价信息的复杂性与不确定性，采用三角模糊数(triangular fuzzy number, TFN)方式获取评价结果.三角模糊数值信息如表 1 所示.

需求 R_α 的重要度 $\tilde{\mu}_\alpha^R$ 及其与功能模块 S_t 的映射关系为

$$\tilde{\mu}_\alpha^R=\frac{1}{\chi^*}\sum_{\chi=1}^{\chi^*}\tilde{\mu}_\alpha^\chi, \tag{9}$$

$$\hat{\varsigma}_{\alpha t}=\frac{1}{\chi^*}\sum_{\chi=1}^{\chi^*}\hat{\varsigma}_{\alpha t}^\chi. \tag{10}$$

式中：$\tilde{\mu}_\alpha^\chi$ 为专家 P_χ 对需求 R_α 的重要度评价值，$\hat{\varsigma}_{\alpha t}^\chi$ 为专家 P_χ 对需求 R_α 与功能模块 S_t 间映射关系的评价.设计需求与功能模块间的关联关系矩阵为

表 1 三角模糊数对应数值表

Tab.1 Corresponding numerical table of triangular fuzzy number

评价信息	TFN
很强(VH)	(0.75, 1.00, 1.00)
较强(H)	(0.50, 0.75, 1.00)
较弱(L)	(0.25, 0.50, 0.75)
很弱(VL)	(0, 0.25, 0.50)
无(N)	(0, 0, 0.25)

$$\hat{\zeta}=\begin{bmatrix}\hat{\varsigma}_{11} & \hat{\varsigma}_{12} & \cdots & \hat{\varsigma}_{1t^*}\\ \hat{\varsigma}_{21} & \hat{\varsigma}_{22} & \cdots & \hat{\varsigma}_{2t^*}\\ \vdots & \vdots & & \vdots\\ \hat{\varsigma}_{\alpha^*1} & \hat{\varsigma}_{\alpha^*2} & \cdots & \hat{\varsigma}_{\alpha^*t^*}\end{bmatrix}. \tag{11}$$

功能模块模糊重要度为

$$\tilde{\eta}_t=\sum_{\alpha=1}^{\alpha^*}\tilde{\mu}_\alpha^R\hat{\varsigma}_{\alpha t}. \tag{12}$$

式中：$\tilde{\mu}_\alpha^R$、$\hat{\varsigma}_{\alpha t}$均为三角模糊数值，运用相对偏好关系分析[26]进行数值处理. 若$\tilde{\alpha}_1,\tilde{\alpha}_2,\cdots,\tilde{\alpha}_x$为同组三角模糊数，且$\tilde{\alpha}_i=(\alpha_{li},\alpha_{hi},\alpha_{vi})$，则此三角模糊数值的均值为

$$\left.\begin{aligned}&\bar{\tilde{\alpha}}=(\bar{\alpha}_1,\bar{\alpha}_{\rm h},\bar{\alpha}_{\rm v});\\ &\bar{\alpha}_1=\frac{1}{x}\sum_{i=1}^{x}\alpha_{1i},\ \bar{\alpha}_{\rm h}=\frac{1}{x}\sum_{i=1}^{x}\alpha_{{\rm h}i},\ \bar{\alpha}_{\rm v}=\frac{1}{x}\sum_{i=1}^{x}\alpha_{{\rm v}i}.\end{aligned}\right\} \tag{13}$$

相对偏好关系分析的重点在于T^*算子的计算，通过运算将三角模糊数转换为精确评价值，

$$T^*\left(\tilde{\alpha}_i,\bar{\tilde{\alpha}}\right)=\frac{1}{2}\times\left(\frac{\alpha_{li}-\bar{\alpha}_{\rm v}}{2\|\boldsymbol{T}^*\|}+\frac{\alpha_{{\rm h}i}-\bar{\alpha}_{\rm h}}{\|\boldsymbol{T}^*\|}+\frac{\alpha_{{\rm v}i}-\bar{\alpha}_1}{2\|\boldsymbol{T}^*\|}+1\right). \tag{14}$$

若$\phi_{\rm lq}^+\geqslant\phi_{\rm vq}^-$，则

$$\|\boldsymbol{T}^*\|=\frac{\left(\phi_{\rm lq}^+-\phi_{\rm vq}^-\right)+2\left(\phi_{\rm hq}^+-\phi_{\rm hq}^-\right)+\left(\phi_{\rm vq}^+-\phi_{\rm lq}^-\right)}{2}; \tag{15}$$

若$\phi_{\rm lq}^+<\phi_{\rm vq}^-$，则

$$\|\boldsymbol{T}^*\|=\frac{2\left(\phi_{\rm hq}^+-\phi_{\rm hq}^-\right)+\left(\phi_{\rm vq}^+-\phi_{\rm lq}^-\right)-3\left(\phi_{\rm lq}^+-\phi_{\rm vq}^-\right)}{2}. \tag{16}$$

式中：$\phi_{\rm lq}^+=\max\limits_i(\alpha_{li})$，$\phi_{\rm hq}^+=\max\limits_i(\alpha_{{\rm h}i})$，$\phi_{\rm vq}^+=\max\limits_i(\alpha_{{\rm v}i})$，$\phi_{\rm lq}^-=\min\limits_i(\alpha_{li})$，$\phi_{\rm hq}^-=\min\limits_i(\alpha_{{\rm h}i})$，$\phi_{\rm vq}^-=\min\limits_i(\alpha_{{\rm v}i})$.

根据偏好相关关系，获得设计需求R_α的相对重要度$\tilde{\mu}_\alpha^R$，运用式（12）得到功能模块的模糊重要度$\tilde{\eta}_t$. 基于式（13）~（16）得到各功能模块的域间映射重要度η_t.

2.4　基于 FDSM-DEMATEL 的功能模块关联关系评价

功能的高度集成与功能模块间的关联关系是复杂产品的重要特征. 在复杂产品的再设计过程中，功能模块间的关联关系评价是实现模块主从识别必不可少的步骤. 本研究结合模糊设计结构矩阵及 DEMATEL 评价功能模块的关联关系，进行多域协同的功能模块重要度评估.

设计结构矩阵（design structure matrix, DSM）[27]是运用数学矩阵描述复杂产品间相互依赖、制约的复杂关系的理论方法，具有建模简单、易于程序化的优点. DSM 可以较完整地反映产品设计及其过程中的潜在问题，在产品设计中的工程更改、设计优化及再设计等方面具有明显的优势. Nomaguchi 等[28]构建多域设计结构矩阵（multi-domain design structure matrix, MDDSM）协调复杂系统设计中设计者对组件归属性的理解差异. 郭伟飞等[29]提出基于设计结构矩阵和遗传算法的综合调度算法，解决复杂产品在实际生产中工序间存在零等待约束的问题. 为了减少多产品协同开发中技术及数据交互对项目进度的影响，Sun 等[30]提出基于扩展 DSM 的信息流调度模型，并以 2 款机床的开发为例进行模型验证. 评价语义具有不确定性，本研究结合模糊评价，构建功能模块间的设计结构矩阵，通过不对称的关联关系描述评价各模块间关联关系.

根据模块域 S 及 DSM，建立模块间模糊设计结构矩阵（fuzzy design structure matrix, FDSM），得到模块间的模糊关联关系$\hat{z}$，如表 2 所示. 表中，r 表示关联程度的模糊数，0 表示完全无关联关系. DEMATEL 基于图论与矩阵工具分析系统元素，可以反映各因素间的相互影响程度. Sangaiah 等[31]基于 DEMATEL 进行系统因素的相关性分析，得到各因素重要度排序. 朱春艳等[32]应用 DEMATEL 分析用户需求的自相关关系，认为需求是非对称的. 本研究采用 DEMATEL 进行功能模块的关联关系计算，以此获得基于关联关系的功能模块重要度. 针对表 2 中的关联关系进行反模糊化处理[33]得到模块间的直接影响关系$\breve{z}$，构成直接影响矩阵$\breve{\boldsymbol{D}}$，标准化后的影响矩阵为

$$\boldsymbol{Y}=\frac{\breve{\boldsymbol{D}}}{\max\limits_{t\leqslant t^*}\sum_{t=1}^{t^*}\breve{\boldsymbol{D}}}. \tag{17}$$

综合影响矩阵为

$$\boldsymbol{Z}=\boldsymbol{Y}+\boldsymbol{Y}^2+\cdots+\boldsymbol{Y}^{t^*}=[Z_{t\vartheta}]^2_{t^*\times t^*}. \tag{18}$$

功能模块的影响度 J_t 为 $\boldsymbol{Z}$ 中每行元素的和，$J_t=\sum_{t=1}^{t^*}Z_{t\vartheta}$，其中$Z_{t\vartheta}$为功能模块 S_t 对功能模块S_ϑ的影响程度；功能模块的被影响度L_t为 $\boldsymbol{Z}$ 中每列元

表 2　模块间模糊关联关系

Tab.2　Fuzzy relationship among modules

S_t	$\hat{z}$		
	S_1	S_2	S_3
S_1	0	r	r
S_2	0	0	r
S_3	r	0	0

素的和，$L_t=\sum_{t=1}^{t^*}Z_{\vartheta t}$，其中$Z_{t\vartheta}$为功能模块$\vartheta$对功能模块$t$的影响程度；功能模块的中心度$N_t=J_t+L_t$，为影响度与被影响度的综合评价[34]，表示各模块的重要程度. 由此，可获得各功能模块的域内相关重要度ρ_t.

3 基于合作博弈的再设计模块主从识别

作为再设计中模块主从识别的重要组成部分，以合作博弈[35]的思想，运用组合赋权方式，建立η_t、ρ_t的综合评价模型.

1）假设通过τ^*种方法赋权各功能模块，得到τ^*个权重向量，$\boldsymbol{\varepsilon}_\tau=[\varepsilon_{\tau 1},\varepsilon_{\tau 2},\cdots,\varepsilon_{\tau t},\cdots,\varepsilon_{\tau t^*}]$，$\tau=1,2,\cdots,\tau^*$，记不同向量的任意组合为

$$\boldsymbol{\varepsilon}=\sum_{\tau=1}^{\tau^*}\lambda_\tau\boldsymbol{\varepsilon}_\tau^{\mathrm{T}};\ \ \lambda_\tau>0,\ \ \sum_{\tau=1}^{\tau^*}\boldsymbol{\varepsilon}_\tau^{\mathrm{T}}=\mathbf{1}. \tag{19}$$

式中：$\boldsymbol{\varepsilon}$为综合权重向量，λ_τ为组合系数.

2）优化组合系数λ_τ，使得$\boldsymbol{\varepsilon}$与每个$\boldsymbol{\varepsilon}_\tau$的离差最小，即

$$\min\left\|\sum_{\tau=1}^{\tau^*}\lambda_\tau\boldsymbol{\varepsilon}_\tau^{\mathrm{T}}-\boldsymbol{\varepsilon}_\gamma^{\mathrm{T}}\right\|_2,\ \ \gamma=1,2,\cdots,\tau^*. \tag{20}$$

3）将式（20）进行线性转化，得到

$$\begin{bmatrix}\boldsymbol{\varepsilon}_1\boldsymbol{\varepsilon}_1^{\mathrm{T}} & \boldsymbol{\varepsilon}_1\boldsymbol{\varepsilon}_2^{\mathrm{T}} & \cdots & \boldsymbol{\varepsilon}_1\boldsymbol{\varepsilon}_{\tau^*}^{\mathrm{T}}\\ \boldsymbol{\varepsilon}_2\boldsymbol{\varepsilon}_1^{\mathrm{T}} & \boldsymbol{\varepsilon}_2\boldsymbol{\varepsilon}_2^{\mathrm{T}} & \cdots & \boldsymbol{\varepsilon}_2\boldsymbol{\varepsilon}_{\tau^*}^{\mathrm{T}}\\ \vdots & \vdots & & \vdots\\ \boldsymbol{\varepsilon}_{\tau^*}\boldsymbol{\varepsilon}_1^{\mathrm{T}} & \boldsymbol{\varepsilon}_{\tau^*}\boldsymbol{\varepsilon}_1^{\mathrm{T}} & \cdots & \boldsymbol{\varepsilon}_{\tau^*}\boldsymbol{\varepsilon}_{\tau^*}^{\mathrm{T}}\end{bmatrix}\begin{bmatrix}\lambda_1\\ \lambda_2\\ \vdots\\ \lambda_{\tau^*}\end{bmatrix}=\begin{bmatrix}\boldsymbol{\varepsilon}_1\boldsymbol{\varepsilon}_1^{\mathrm{T}}\\ \boldsymbol{\varepsilon}_2\boldsymbol{\varepsilon}_2^{\mathrm{T}}\\ \vdots\\ \boldsymbol{\varepsilon}_{\tau^*}\boldsymbol{\varepsilon}_{\tau^*}^{\mathrm{T}}\end{bmatrix}. \tag{21}$$

由式（21）得到$\{\lambda_1,\lambda_2,\cdots,\lambda_{\tau^*}\}$，对其进行归一化处理得到

$$\lambda_\tau^*=\frac{\lambda_\tau}{\sum\limits_{\tau=1}^{\tau^*}\lambda_\tau}. \tag{22}$$

最优综合权重向量为

$$\boldsymbol{\varepsilon}^*=\sum_{\tau=1}^{\tau^*}\lambda_\tau^*\boldsymbol{\varepsilon}_\tau^{\mathrm{T}}. \tag{23}$$

在再设计过程中，第t个功能模块的重要度为

$$W_t=\eta_t\varepsilon_{\eta_t}^*+\rho_t\varepsilon_{\rho_t}^*. \tag{24}$$

由此，完成复杂产品再设计模块的主从排序.

4 案例研究

为了满足市场的快速发展需求，对如图 2 所示的 CKA6180 数控机床进行再设计研究.

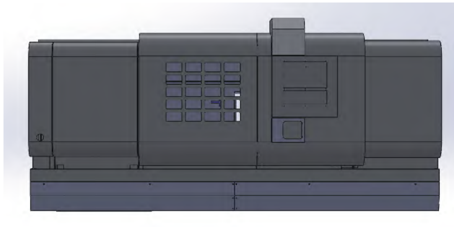

图 2　CKA6180 数控机床
Fig.2　CKA6180 CNC machine tool

4.1　数控机床功能模块分解

与机床工程师探讨后，对 CKA6180 数控机床进行三维模型分解，在保证各模块间功能独立性的前提下，获得模块域S，分解结果如图 3 所示，功能模块说明如表 3 所示.

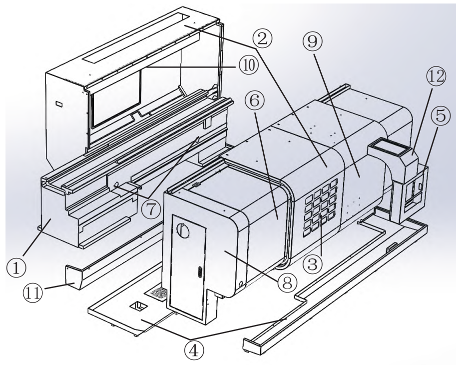

图 3　CKA6180 数控机床功能模块分解
Fig.3　Decomposition of CKA6180 CNC machine tool functional modules

4.2　功能模块域间映射重要度评估

根据产品实际设计情况，确定用户、设计师、企业决策者、工程师 4 类人群为本研究的认知主体. 由于工作经验及职责分工不同，为了尽量减少偏差，保证评价结果客观准确，在实际研究中，用户及企业决策者参与情感需求及物理需求的确定，设计师主要参与情感需求的确定，工程师主要参与物理需求的确定.

从数控机床销售网站、各机床企业官网渠道搜集同类型机床图片 76 张，由专家小组对其进行评估筛选，最终确定 15 张作为研究样本，形成情感意象评估样本集$A=\{a_1,a_2,\cdots,a_{15}\}$，如图 4 所示. 从各大机床品牌网站、产品宣传册、学术文献等方面搜集描述机床情感意象的形容词共 92

表 3　CKA6180 数控机床的功能模块说明表

Tab.3　Description table of function module for CKA6180 CNC machine tool

序号	模块名称	说明
①	加工模块S_1	核心加工部分，根据技术保密需求仅展示床身
②	防护模块S_2	保护机床整体及加工人员，防止加工废料飞溅；分为前防护和后防护
③	观察模块S_3	观察加工状态
④	集屑模块S_4	搜集加工废料并进行清洁处理
⑤	操控模块S_5	机床操作系统
⑥	标识模块S_6	企业标识及产品型号信息，主要位于机床的正面防护罩
⑦	吊装模块S_7	支撑机床的吊装过程
⑧	检修模块S_8	维护检修机床核心加工部位
⑨	警示模块S_9	警示灯一般安装在机床顶部，警示标贴及说明一般张贴在机床的正面防护罩上
⑩	照明模块S_{10}	位于后防护罩；照明加工空间
⑪	封装模块S_{11}	辅助机床形成密闭空间，一般位于机床下部
⑫	电控模块S_{12}	主要为加工及操控的线路排布、集成

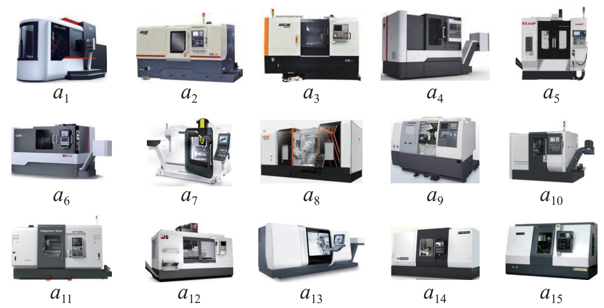

图 4　数控机床研究样本集

Fig.4　Research sample set of CNC machine tool

个. 通过词汇间相融性分析，剔除相近或相似的形容词，经过专家小组讨论，确定代表性情感形容词共 10 个，形成情感需求意象词汇集 B={简洁的，现代的，科技的，沉稳的，精致的，大气的，个性的，机械感的，厚重的，协调的}. 根据样本集与情感需求意象集，建立李克特量表，分别对用户 17 人、设计师 21 人进行意象需求评价，对所获得的评价数据进行均值化处理. 经式（4）~（7）计算分别得到用户、设计师的情感需求意象词汇的权重评价 ω_M、ω_G，如表 4 所示. 对用户而言，“科技的”“现代的”的权重值位于前 2 位，且与其他词汇权重差距较大，因此定义用户的情感需求为 “现代的”“科技的”. 对设计师而言，“沉稳的”权重值远远高于其他词汇，因此定义设计师的情感需求为

表 4　用户及设计师情感需求权重

Tab.4　Weight of emotional needs of users and designers

R_K	ω_M	ω_G
简洁的	0.076	0.087
现代的	**0.140**	0.060
科技的	**0.146**	0.094
沉稳的	0.055	**0.171**
精致的	0.121	0.112
大气的	0.124	0.079
个性的	0.077	0.093
机械感的	0.054	0.136
厚重的	0.078	0.067
协调的	0.129	0.101

“沉稳的”. 企业决策者定义“现代的”“品牌性”为情感需求. 情感需求集 R_K ={科技的，沉稳的，现代的，品牌性}. 受到企业工程师与决策者人数限制，通过市场调研并与工程师、企业决策者探讨，得到物理需求集 R_F={（观察）视野清晰，（工件）取用方便，（系统）操作便捷，（品牌）识别性强，（整机）吊装方便，（废料）回收便捷，（维护）拆卸方便}.

综合 R_K、R_F，由于“品牌性”与“（品牌）识别性强”的意义相同，合并后取后者，得到设计需求域 R={科技的 R_1，沉稳的 R_2，现代的 R_3，（观察）视野清晰 R_4，（工件）取用方便 R_5，（系统）操作便捷 R_6，（品牌）识别性强 R_7，（整机）吊装方便 R_8，（废料）回收便捷 R_9，（维护）拆卸方便 R_{10}}. 由 8 位机床行业的资深专家组成专家组，利用表 1 对设计需求域进行重要度评估，由式（9）、（13）、（14）得到各设计需求的模糊重要度及相对重要度，如表 5 所示. 由专家组进行设计需求与功能模块间的关联关系模糊语义评价，由式（10）、（12）得到设计需求映射的各功能模块重要度模糊评价，如表 6 所示. 运用式（13）、（14）转化表中模糊数据并进行归一化处理，得到各功能模块的域间映射重要度 η_t 依次为 0.068, 0.132, 0.107, 0.095, 0.107, 0.084, 0.049, 0.080, 0.057, 0.073, 0.095, 0.054.

4.3　功能模块关联关系评价

由 5 位机床行业专家组成的专家组针对所建立的设计结构矩阵进行功能模块间的关联关系模糊评价，评价准则见表 1. 数据经反模糊化处理后得到的标准化矩阵如表 7 所示. 根据式（18）获得综合影响矩阵，则功能模块的影响度、被影响度

表 5 设计需求重要度评价结果

Tab.5 Evaluation results of importance of design requirements

R_α	$\tilde{\mu}_\alpha^R$	$\hat{\mu}_\alpha^R$
R_1	(0.594, 0.844, 1.000)	0.691
R_2	(0.375, 0.625, 0.875)	0.505
R_3	(0.656, 0.906, 1.000)	0.735
R_4	(0.344, 0.594, 0.844)	0.475
R_5	(0.250, 0.500, 0.750)	0.386
R_6	(0.438, 0.688, 0.938)	0.564
R_7	(0.563, 0.813, 0.969)	0.661
R_8	(0.094, 0.344, 0.594)	0.237
R_9	(0.344, 0.594, 0.844)	0.475
R_{10}	(0.094, 0.344, 0.594)	0.237

及中心度如表 8 所示. 将中心度归一化处理，得到各模块的域内相关重要度 ρ_t 依次为 0.128, 0122, 0.087, 0.080, 0.096, 0.041, 0.051, 0.086, 0.075, 0.085, 0.084, 0.065.

4.4 基于合作博弈的功能模块重要度综合评价

将功能模块的 2 组评价值作为合作博弈的双方，由式(19)得到基础权重向量集，基于式(20)~(24)获得再设计中各功能模块的综合重要度 W_t 依次为 0.098, 0.127, 0.097, 0.088, 0.101, 0.063, 0.050, 0.083, 0.066, 0.079, 0.090, 0.060.

结合域间映射重要度 η_t、域内相关重要度 ρ_t 及综合重要度 W_t，建立如图 5 所示的模块重要度 W 对比图. 可以看出，当仅考虑设计需求映射的再设计模块主从评价时，应优先考虑的是防护模块、操控模块、观察模块等. 原因是该类模块不仅体现了产品的功能，也体现了产品的形态感知、品牌展示. 针对数控机床，由于功能结构的高度集成化，功能模块间具有高度相关性. 当仅考虑模块域内关联关系时，加工模块作为产品的核心功能应被优先考虑. 原因是其他功能模块均基于加工功能构建，加工模块与大部分功能模块均存在相互关联关系，使得自身的重要度显著提高.

表 6 设计需求映射的功能模块重要度模糊评价

Tab.6 Fuzzy evaluation of importance of function modules of design requirement mapping

R_α	$\tilde{\eta}_t$				
	S_1	S_2	S_3	…	S_{12}
R_1	(0.000, 0.130, 0.302)	(0.432, 0.604, 0.691)	(0.238, 0.410.0.583)	…	(0.000, 0.151, 0.324)
R_2	(0.095, 0.205, 0.331)	(0.300, 0.426, 0.505)	(0.126, 0.252, 0.379)	…	(0.016, 0.142, 0.268)
R_3	(0.046, 0.230, 0.414)	(0.506, 0.690, 0.735)	(0.345, 0.529, 0.712)	…	(0.046, 0.207, 0.391)
R_4	(0.015, 0.205, 0.303)	(0.163, 0.282, 0.401)	(0.341, 0.460, 0.475)	…	(0.000, 0.000, 0.119)
⋮	⋮	⋮	⋮	⋮	⋮
R_{10}	(0.022, 0.074, 0.133)	(0.126, 0.185, 0.237)	(0.067, 0.126, 0.185)	…	(0.015, 0.074, 0.133)

表 7 功能模块关联关系标准化矩阵

Tab.7 Standardized matrix of association among functional modules

S_t	$\tilde{z}$								
	S_1	S_2	S_3	S_4	S_5	…	S_{10}	S_{11}	S_{12}
S_1	0	0.134	0.145	0.111	0.103	…	0.070	0.042	0.039
S_2	0.184	0	0.131	0.111	0.070	…	0.089	0.123	0.039
S_3	0.134	0.111	0	0.031	0.059	…	0.081	0.022	0.022
S_4	0.192	0.167	0.039	0	0.042	…	0.014	0.089	0.022
S_5	0.164	0.100	0.089	0.081	0	…	0.078	0.022	0.059
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
S_{10}	0.167	0.153	0.142	0.031	0.089	…	0	0.081	0.031
S_{11}	0.123	0.156	0.164	0.164	0.039	…	0.070	0	0.047
S_{12}	0.123	0.089	0.033	0.033	0.156	…	0.042	0.061	0

表 8　功能模块间的自相关关系

Tab.8　Autocorrelation among functional modules

S_t	J_t	L_t	N_t
S_1	6.427	3.707	10.134
S_2	5.404	4.271	9.675
S_3	4.142	2.746	6.888
S_4	3.276	3.067	6.343
S_5	3.828	3.726	7.554
S_6	1.481	1.794	3.275
S_7	1.408	2.623	4.031
S_8	3.631	3.152	6.783
S_9	2.425	3.474	5.899
S_{10}	2.819	3.920	6.739
S_{11}	2.823	3.840	6.663
S_{12}	1.903	3.248	5.151

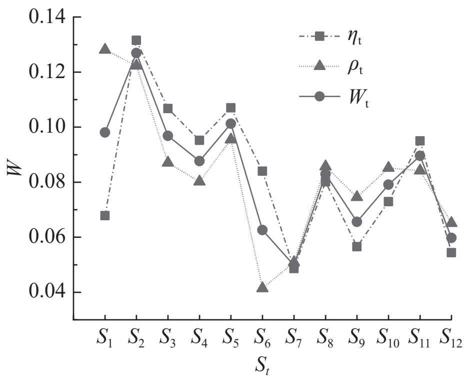

图 5　数控机床模块重要度对比关系图

Fig.5　Importance comparison diagram of CNC machine tool modules

运用合作博弈对各模块域间映射重要度和域内相关重要度进行综合评价，再设计过程中机床各功能模块主从关系依次为防护模块、操控模块、加工模块、观察模块、封装模块、集屑模块、检修模块、照明模块、警示模块、标识模块、电控模块、吊装模块.

5 结　论

（1）提出基于情感需求与物理需求相结合的设计需求域构建思路，丰富了复杂产品现代设计需求内涵. 结合模糊评价及相对偏好分析可以有效获取各功能模块的域间映射重要度，使再设计中的相关需求得到较全面地传递.

（2）结合 FDSM-DEMATEL 构建功能模块的关联关系评价体系，可以有效获取各模块的域内相关重要度，解决了因缺失功能模块关联关系分析导致的评估不全面问题.

（3）运用合作博弈思维构建基于域间映射重要度及域内相关重要度的综合评价方法，能够客观准确地获取复杂产品再设计过程中各模块的主从关系，有效指导企业进行产品再设计规划.

（4）模块的主从关系识别是复杂产品再设计过程中经常遇到的问题，该方法对于复杂产品再设计过程的决策具有明显优势，对于提升复杂产品的市场竞争力具有重要意义. 但评价过程采用的模糊打分方式主观性较强，对模块间复杂耦合性的分析不足，仅以较直观的关联关系评价为主. 后续将重点进行创新评价方法的挖掘运用以及模块间复杂耦合关系的深入研究，根据模块主从关系指导的复杂产品再设计方案也将在后续研究中展示.

参考文献 (References):

[1] 谭建荣, 刘振宇, 徐敬华. 新一代人工智能引领下的智能产品与装备 [J]. 中国工程科学, 2018, 20(4): 35–43.
TAN Jian-rong, LIU Zhen-yu, XU Jing-hua. Intelligent products and equipment led by new-generation artificial intelligence [J]. **Strategic Study of CAE**, 2018, 20(4): 35–43.

[2] WANG Y, MA H S, YANG J H, et al. Industry 4.0: a way from mass customization to mass personalization production [J]. **Advances in Manufacturing**, 2017, 5(4): 311–320.

[3] LIU Z H, ZHANG M T, LI Y P, et al. Research on the module configuration of complex products considering the evolution of the product family [J]. **Journal of Intelligent and Fuzzy Systems**, 2020, 39(3): 4577–4595.

[4] 朱思羽, 胡洁, 戚进. 基于美学、人体工学及性能的多因素融合设计 [J]. 机械工程学报, 2020, 56(21): 199–207.
ZHU Si-yu, HU Jie, QI Jin. Multi-factor coupling design based on aesthetic measure, ergonomics, and performance [J]. **Journal of Mechanical Engineering**, 2020, 56(21): 199–207.

[5] 赖荣燊, 林文广, 吴永明. 面向绿色性能优化的产品族模块再设计优先次序识别 [J]. 中国机械工程, 2019, 30(11): 1329–1335.
LAI Rong-shen, LIN Wen-guang, WU Yong-ming. Redesign priority identification of product family modules for green performance optimization [J]. **China Mechanical Engineering**, 2019, 30(11): 1329–1335.

[6] 周鹏辉, 马红占, 陈东萍, 等. 基于模糊随机故障模式与影响分析的产品再设计模块识别 [J]. 上海交通大学学报, 2017, 51(10): 1189–1195.
ZHOU Peng-hui, MA Zhan-hong, CHEN Dong-ping, et al. Identification of product resign modules based on fuzzy random

failure mode and effects analysis [J]. **Journal of Shanghai Jiao Tong University**, 2017, 51(10): 1189–1195.

[7] LI Y P, WANG Z T, ZHONG X Y, et al. Identification of influential function modules within complex products and systems based on weighted and directed complex networks [J]. **Journal of Intelligent Manufacturing**, 2019, 30(6): 2375–2390.

[8] SHIN J H, KIRITSIS D, XIROUCHAKIS P. Design modification supporting method based on product usage data in closed-loop PLM [J]. **International Journal of Computer Integrated Manufacturing**, 2015, 28(6): 551–568.

[9] MA H Z, CHU X N, XUE D Y, et al. Identification of to-be-improved components for redesign of complex products and systems based on fuzzy QFD and FMEA [J]. **Journal of Intelligent Manufacturing**, 2019, 30(2): 623–639.

[10] YAN H B, MA T J. A group decision-making approach to uncertain quality function deployment based on fuzzy preference relation and fuzzy majority [J]. **European Journal of Operational Research**, 2015, 241(3): 815–829.

[11] 褚学宁, 陈汉斯, 马红占. 性能数据驱动的机械产品关键设计参数识别方法 [J]. 机械工程学报, 2021, 57(3): 185–196.
CHU Xue-ning, CHEN Han-si, MA Hong-zhan. Identification of critical design parameter for mechanical products based on performance data [J]. **Journal of Mechanical Engineering**, 2021, 57(3): 185–196.

[12] 张付英, 段晶莹, 陈建垒, 等. 面向产品可持续设计的关键功能模块识别方法 [J]. 计算机集成制造系统, 2019, 25(7): 1828–1838.
ZHANG Fu-ying, DUAN Jing-ying, CHEN Jian-lei, et al. Critical functional modules identification method for product sustainable design [J]. **Computer Integrated Manufacturing Systems**, 2019, 25(7): 1828–1838.

[13] 樊佳爽, 余隋怀, 初建杰, 等. 云服务模式下设计方案的优选决策方法 [J]. 浙江大学学报:工学版, 2020, 54(1): 143–151.
FAN Jia-shuang, YU Sui-huai, CHU Jian-jie, et al. Optimal decision-making method of design scheme in cloud service mode [J]. **Journal of Zhejiang University: Engineering Science**, 2020, 54(1): 143–151.

[14] 耿秀丽, 邱华清. 考虑顾客满意度的顾客需求重要度确定方法 [J]. 计算机集成制造系统, 2019, 25(8): 2025–2035.
GENG Xiu-li, QIU Hua-qing. Customer requirements importance degree calculation method considering customer satisfaction [J]. **Computer Integrated Manufacturing Systems**, 2019, 25(8): 2025–2035.

[15] 陈国东, 陈思宇, 王军, 等. 面向复合意象的产品形态多目标优化 [J]. 中国机械工程, 2015, 26(20): 2763–2770.
CHEN Guo-dong, CHEN Si-yu, WANG Jun, et al. Multi-objective optimization method of composite imagery-oriented product form [J]. **China Mechanical Engineering**, 2015, 26(20): 2763–2770.

[16] SAUER N S, RATNESHWAR S, SEN S. Drivers of consumer–brand identification [J]. **International Journal of Research in Marketing**, 2012, 29: 406–418.

[17] ZHANG X X, YANG M G, SU J N, et al. Research on product color design decision driven by brand image [J]. **Color Research and Application**, 2020, 45(6): 1202–1216.

[18] 周爱民, 刘宏斌, 张书涛, 等. 面向汽车主客观审美评价的不确定性推理模型 [J]. 浙江大学学报:工学版, 2021, 55(3): 419–429.
ZHOU Ai-min, LIU Hong-bin, ZHANG Shu-tao, et al. Uncertainty reasoning model of subjective and objective aesthetic evaluation of car [J]. **Journal of Zhejiang University: Engineering Science**, 2021, 55(3): 419–429.

[19] 苏建宁, 张新新, 景楠, 等. 认知差异下的产品造型意象熵评价研究 [J]. 机械设计, 2016, 33(3): 105–108.
SU Jian-ning, ZHANG Xin-xin, JING Nan, et al. Research on the entropy evaluation of product styling image under the cognitive difference [J]. **Journal of Machine Design**, 2016, 33(3): 105–108.

[20] 柳禄, 章永年, 丁为民, 等. 多目标驱动的拖拉机产品族外形基因设计 [J]. 农业工程学报, 2017, 33(17): 82–90.
LIU Lu, ZHANG Yong-nian, DING Wei-min, et al. Design of multi-objective driven product family shape gene for tractor [J]. **Transactions of the Chinese Society of Agricultural Engineering**, 2017, 33(17): 82–90.

[21] 胡洁, 陈斌. 创新设计中的源泉、机制和评价问题研究综述 [J]. 包装工程, 2020, 41(18): 60–70.
HU Jie, CHEN Bin. Source, operating mechanism, and evaluation of innovative design [J]. **Packaging Engineering**, 2020, 41(18): 60–70.

[22] 罗仕鉴. 群智设计新思维 [J]. 机械设计, 2020, 37(3): 121–127.
LUO Shi-jian. New thought of crowd intelligence design [J]. **Journal of Machine Design**, 2020, 37(3): 121–127.

[23] KHALAJ J, PEDGLEY O. A semantic discontinuity detection (SDD) method for comparing designers' product expressions with users' product impressions [J]. **Design Studies**, 2019, 62: 36–67.

[24] QIU K, SU J N, ZHANG X X, et al. Evaluation and balance of cognitive friction: evaluation of product target image form combining entropy and game theory [J]. **Symmetry**, 2020, 12(9): 1398.

[25] 肖人彬, 蔡池兰, 刘勇. 公理设计的研究现状与问题分析 [J]. 机械工程学报, 2008, 44(12): 1–11.
XIAO Ren-bin, CAI Chi-lan, LIU Yong. Current research situation and problem analysis of axiomatic design [J]. **Journal of Mechanical Engineering**, 2008, 44(12): 1–11.

[26] 耿秀丽, 徐士东, 叶春明. 顾客需求驱动的产品服务系统模块选配方法 [J]. 计算机集成制造系统, 2016, 22(1): 55–61.
GENG Xiu-li, XU Shi-dong, YE Chun-ming. Module configuration approach for product service system design driven by customer requirements [J]. **Computer Integrated Manufacturing Systems**, 2016, 22(1): 55–61.

(下转第 2391 页)

Intelligence, 2015, 37(9): 1834–1848.

[21] LIANG P P, BLASCH E, LING H B. Encoding color information for visual tracking: algorithms and benchmark [J]. **IEEE Transactions on Image Processing**, 2015, 24(12): 5630–5644.

[22] MUELLER M, SMITH N, GHANEM B. A benchmark and simulator for UAV tracking [C]// **2016 European Conference on Computer Vision.** Amsterdam: Springer, 2016: 445–461.

[23] MA C, HUANG J B, YANG X, et al. Hierarchical convolutional features for visual tracking [C]// **2015 IEEE International Conference on Computer Vision**. Santiago: IEEE, 2015: 3074–3082.

[24] QI Y, ZHANG S, QIN L, et al. Hedged deep tracking [C]// **2016 IEEE Conference on Computer Vision and Pattern Recognition.** Las Vegas: IEEE, 2016: 4303–4311.

[25] DANELLJAN M, HÄGER G, KHAN F S, et al. Convolutional features for correlation filter based visual tracking [C]// **2015 IEEE International Conference on Computer Vision Workshop.** Santiago: IEEE, 2015: 621–629.

[26] DANELLJAN M, BHAT G, KHAN F S, et al. ECO: efficient convolution operators for tracking [C]// **2017 IEEE Conference on Computer Vision and Pattern Recognition.** Honolulu: IEEE, 2017: 6931–6939.

[27] DANELLJAN M, HÄGER G, KHAN F S, et al. Adaptive decontamination of the training set: a unified formulation for discriminative visual tracking [C]// **2016 IEEE Conference on Computer Vision and Pattern Recognition.** Las Vegas : IEEE, 2016: 1430–1438.

[28] MA C, YANG X K, ZAHNG C Y, et al. Long-term correlation tracking [C]// **2015 IEEE Conference on Computer Vision and Pattern Recognition.** Boston: IEEE, 2015: 5388–5396.

[29] MA H Y, ACTON S T, LIN Z L. SITUP: scale invariant tracking using average peak-to-correlation energy [J]. **IEEE Transactions on Image Processing**, 2020, 29: 3546–3557.

[30] MA H Y, LIN Z L, ACTON S T. FAST: fast and accurate scale estimation for tracking [J]. **IEEE Signal Processing Letters**, 2020, 27: 161–165.

[31] FU C H, XU J T, LIN F L, et al. Object saliency-aware dual regularized correlation filter for real-time aerial tracking [J]. **IEEE Transactions on Geoscience and Remote Sensing**, 2020, 58(12): 8940–8951.

[32] BERTINETTO L, VALMADRE J, HENRIQUES J F, et al. Fully-convolutional siamese networks for object tracking [C]// **2016 European Conference on Computer Vision**. Amsterdam: Springer, 2016: 850–865.

(上接第 2366 页)

[27] 孙亚东, 张旭, 宁汝新, 等. 基于层次化设计结构矩阵的复杂产品研发过程研究 [J]. 机械工程学报, 2011, 47(16): 166–175.
SUN Ya-dong, ZHANG Xu, NING Ru-xin, et al. Research on development process of complex product based on multi-level design structure matrix [J]. **Journal of Mechanical Engineering**, 2011, 47(16): 166–175.

[28] NOMAGUCHI Y, SAITO M, FUJITA K. Multi-domain DSM method for design process management of complex system [J]. **Journal of Industrial and Production Engineering**, 2015, 32(7): 465–472.

[29] 郭伟飞, 雷琦, 宋豫川, 等. 基于虚拟零部件的零等待约束复杂产品综合调度算法 [J]. 机械工程学报, 2020, 56(4): 246–257.
GUO Wei-fei, LEI Qi, SONG Yu-chuan, et al. Integrated scheduling algorithm of complex product with no-wait constraint based on virtual component [J]. **Journal of Mechanical Engineering**, 2020, 56(4): 246–257.

[30] SUN Q C, HUANG W Q, JIANG Y J, et al. Information flow scheduling in concurrent multi-product development based on DSM [J]. **Chinese Journal of Mechanical Engineering**, 2017, 30(5): 1101–1111.

[31] SANGAIAH A K, GOPAL J, BASU A, et al. An integrated fuzzy DEMATEL, TOPSIS, and ELECTRE approach for evaluating knowledge transfer effectiveness with reference to GSD project outcome [J]. **Neural Computing and Applications**, 2017, 28(1): 111–123.

[32] 朱春艳, 杨明顺, 高新勤, 等. 基于 DEMATEL 和熵的顾客需求重要度修正 [J]. 工业工程与管理, 2012, 17(3): 97–101.
ZHU Chun-yan, YANG Ming-shun, GAO Xin-qin, et al. Modifying the importance ratings of customer requirements based on DEMATEL and entropy [J]. **Industrial Engineering and Management**, 2012, 17(3): 97–101.

[33] 张蕾, 冯良清, 王娟. 服务型制造网络模块化质量属性识别研究 [EB/OL]. [2021-10-06]. https://kns.cnki.net/kcms/detail/11.5946.TP.20210622.1026.004.html.

[34] 张英芝, 荣峰, 申桂香, 等. 基于市场竞争及自相关关系的数控机床可用性需求指标权重计算 [J]. 计算机集成制造系统, 2016, 22(7): 1687–1694.
ZHANG Ying-zhi, RONG Feng, SHEN Gui-xiang, et al. Weight calculation for availability demand index of CNC machine tools based on market competition and self-correlation [J]. **Computer Integrated Manufacturing Systems**, 2016, 22(7): 1687–1694.

[35] SUN Q Q, YANG G L, WANG X Y, et al. Cooperative game-oriented optimal design in constraint-following control of mechanical systems [J]. **Nonlinear Dynamics**, 2020, 101(2): 977–995.