An Evolutionary Design Method of Product Form Inspired by Spider-webs

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Abstract. Product serialization design is an effective method for product family development. To explore the development law of product serialization, the kansei image change law within the series, and the interaction mechanisms of kansei image and form between the series, this paper proposes an evolutionary design method of product form inspired by Spider-webs. Inspired by the special structure and mechanical properties of Spider-webs in nature, at the macro level, we use the structure of the Spider-webs to describe the relationship between products in the product family. At the micro level, based on the mechanical properties of spider-webs, we analyzed the development law of the product form within and between the series in the product family and then proposed a calculation method for the crossover coefficient and variation coefficient (in the genetic algorithm) for product form evolution. This method provides a scientific basis for determining the crossover coefficient and the variation coefficient from a new perspective. The case study results show that this model can effectively simulate the changing laws of design cognition and the evolution laws of product form, thereby providing a theoretical basis for the intelligent design of product form in a product family.

Keywords: genetic algorithm; evolutionary strategies; spider-web; product family; kansei image.
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1 INTRODUCTION

Under the intensification of industry, products are becoming more homogeneous, and market competition is becoming increasingly fierce. Traditional market-oriented product research and development strategies have been unable to meet these new demands. Increasingly, more scholars and enterprises are paying attention to developing unique styles for their products, building brand differentiation, and establishing unique brand images through innovative design.

As an expression of the product design idea, a product form provides a communication medium between designers and consumers by conveying meanings at spiritual and cultural levels [1]. In the consumer-centered era, product updates and iteration speeds are relatively fast, and there is little difference at the functional and technical level between products in the same field [2]. Product family design is one of the most effective methods to enhance product competitiveness and meet the individual needs of consumers.

In enterprises, serialized products are defined as types of products that have a shared common technology platform but specific functions and characteristics to satisfy a group of relevant market segments and meet customers' kansei requirements [3]. According to market trends and consumers' kansei needs, serialized product design effectively applies shared, reusable, and inheritable common characteristics of some attributes of related products, integrates changeable personality modules, and quickly derives personalized products that meet the different needs of consumers. This can provide a quick response to changes in market demand, ensure the stable development of the enterprise, and save design costs to the greatest extent. The concept of product serialization has been expanded from multiple perspectives and classified according to different classification standards to support the development of new products. Zhang proposed that product serialization design can be divided into three categories: market-driven product serialization design, product serialization design driven by diversity and upgradability, and product serialization form design [4]. With the development of internet technology, data-driven product family design research is gradually emerging through the integration of big data and artificial intelligence algorithms [5]. According to the driving model, product serialization design mainly encompasses the four types mentioned above.

Xu proposed the idea of a pan-ethnic group product form design by applying the shape grammar modification law to develop form elements with high weight values and applying pan-ethnic group product design methods to provide innovative designs for those with low weight values [6]. In this way, product forms with specific kansei can be developed, and a series of products can be designed quickly to meet the individual needs of consumers. Based on the product family iteration language, Zhang explained the research of product family from a macro perspective and proposed a program that can systematically and quickly correct unpredictable changes in the development of a product family to improve the market adaptability and evolution capabilities of the series of products [7].

In terms of product serialization design driven by diversity and upgradability, Zhang proposed obtaining brand image genes through quantifiable indicators to guide the form design of a product family [8]. To meet the needs of users and improve brand recognition, Zhu explored the genetic and brand characteristics of product form design from the two perspectives of consumers' kansei image recognition and brand form characteristics to give the product form better continuity [9]. Luo established a mapping model between consumer preferences and product family form genes by dividing the expression levels of product family form genes and constructed a preference-driven product family form gene design method [10].

In terms of data-driven product family design, based on market data, Song proposed a data-driven design system to assist designers in designing, developing and planning products. The system evaluates optimal products with a functional network based on the previous product functional relationships [11]. According to the design requirements of the product family, Xiao carried out data mining to develop the platform architecture for data-driven product family design [5]. Ma proposed a prediction model to predict the best product family series design based on user preference data [12].

The market represents the consumers' kansei demands that drive product serialization design. In this area, Liu comprehensively analyzed the three target elements of brand recognition, consumers' kansei, and social situation and proposed a multi-objective-driven product family form gene evolution design process [13]. Su proposed the evolution design of product form based on consumers' demands for multiple images [14]. Su also proposed that the form design of a product family based on perceptual images should include perceptual image mining (to determine the design direction of the product family), analysis of the product form variables (to obtain the individual and common elements in the product family), and product family form design (to obtain a series of products to meet consumer demands) [15]. Masakazu put forward a new product design method based on Kansei engineering. By analyzing customers' Kansei evaluation of existing products, a three-layer relationship model of customers' Kansei and product aesthetics was established. Finally, genetic algorithm was used to optimize the design of new products [16]. Wang applied the genetic algorithm (GA) and a back propagation (BP) neural network to establish a nonlinear mapping relationship between product form and images and ultimately realized the multi-objective optimization design of product form [17]. Based on Bayesian networks, Li proposed a dynamic analysis model of product design evolution to study the dynamic relationship between consumer demand and product design [18]. Feng parameterized the shape of motorcycle seat, evaluated it with the method of Kansei Engineering, established the equation of Kansei regression analysis, and finally forecasted the shape of motorcycle with grey model [19]. In order to consider the diversity of customer perception in product development, Masakazu proposed a method of customer grouping and product design based on rough set theory [20]. The product kansei image represents consumer demand, and the product form represents feedback to that demand. The product kansei image drives the innovative development of product form.

In existing serialized product development design and product family evolution design research, most scholars focus on mapping the relationship between products and the market, consumers' kansei demand, brand recognition, and other factors. However, many issues are frequently ignored, such as the relationship between series and the inheritance and innovation of product forms. It makes the product series lose the brand style of the enterprise in the update iteration. Therefore, in this paper, our research goal is to shift the focus from single product to a product family to explore the inheritance and innovation laws of product form among multiple series in a product family and in the iterative process of a single series. The style inheritance and interactions between the series in the iterative process of the product family are the focus of this paper. Through the study of these changes, we can assist designers in product form development, reduce the kansei image deviation caused by designers' personal cognitive factors, and make the product development not only have the style inheritance of this series, but also have new innovation.

The main contributions of this paper are summarized as follows:

1. Based on a spider-web structure, we propose a product kansei image spider-web model that explores the complex relationship between different series of kansei images in the development process of product families and uses the special structure of the spider-web to characterize this complex relationship.

2. Based on the above-mentioned product kansei image spider-web model, we study the change law of product kansei image and product form in the product family over time. Firstly, we explored the product kansei image change law within a single series in the iterative process of product form in the product family. Secondly, we explore the product kansei image interaction law between multiple series in the product family. These two processes drive the continuous innovation of product forms in the iterative process.

3. Finally, the product form spider-web evolution model is established to simulate design thinking and carry out the product form evolution design. This model will help solve the problems of style image changes caused by a replacement of designers and decision makers in product development and reduce the impact of human factors on products. This provides a theoretical basis for the intelligent design of product form in the product family.

The rest of this paper is organized as follows. Section 2 presents the relationship between the changes of product kansei image and product form, the spider-web structure, and the spider silk mechanical properties in the product serialization development. In Section 3, based on the spider-web structure and mechanical properties, we propose a detailed process for constructing the product kansei image spider-web model and the product form spider-web evolution model separately. In Section 4, we illustrate the research process of these models using a practical case of the product form design of Audi A series car headlights. Section 5 discusses these models. Finally, Section 6 provides some brief conclusions.

2 PRODUCT SERIALIZATION DESIGN AND SPIDER-WEB

2.1 Product Serialization and Spider-web Structure

With the rapid development of global economic integration, consumer demand (personalization and diversification), and market factors (technology, economy, policy, social environment, and technology), the evolutionary design contradictions of product families have also undergone significant changes. In the initial stage, product development must simply meet the market demands. Over time, however, some external factors force enterprises to develop their products to meet new consumer demands [18]. In this process, a product family tree is gradually formed. For example, Leica, a well-known camera brand in Germany, constituted a Leica Family Tree through a century of development. In this product family tree, there is a vertical intergenerational inheritance relationship between products, and a variety of products for different user needs are produced horizontally. This product family tree is the result of serialization design. Product serialization design gives related products the common characteristics of being shareable, reusable, and inheritable. According to the market trends and the special requirements of consumers, this design can be flexibly modified to quickly develop new products that can not only meet the market demands but can also maintain the continuity of the brand image [21]. This product serialization design has been successfully applied to products from companies such as Sony, BMW, Volkswagen, and Audi. From the perspective of product development history, excellent form features are inherited in the same series and have correlations in different series.

In nature, spider-webs and product family trees have some similarities in their structures. There are various shapes of spider-webs, such as polygonal webs, circular webs, and deformed webs. As shown in Figure 1, the structure of a spider-web is complex but is governed by certain rules. A web is composed of mooring, frame silk, capture silk, and radial silk [22]. The predation surface is composed of radial silk and capture silk, which are cross-connected to form a web area to intercept prey. In this paper, the spider-web structure is simplified. As shown in Figure 2, this structure is mainly composed of radial silk and capture silk. When the radial silk extends outward, the nodes on the radial silk are correlated with each other via the capture silk. This interrelated characteristic has a high degree of similarity with the product family. We examine the headlights of Audi A series cars as an example, as shown in Figure 3. The thick solid lines represent the product series; the thin solid lines represent the connection between the two series; the dashed line between the two series indicates that one of the new products has not yet developed; T represents the product generation. At the macro level, both the iterative evolution of the product series and the interrelationship of different product series are similar to the node relationships in the spider-web structure.

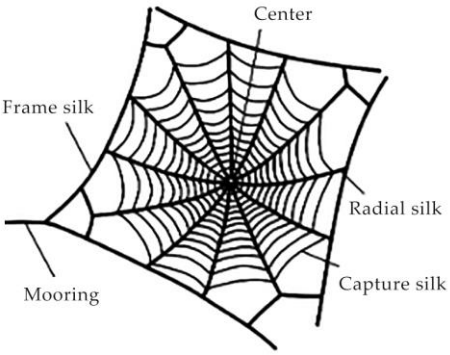


Figure 1: Spider-web structure in nature.

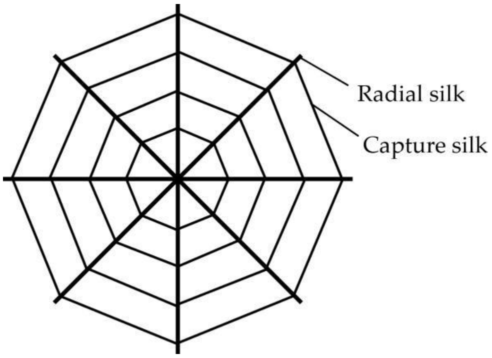


Figure 2: Simplified spider-web structure.

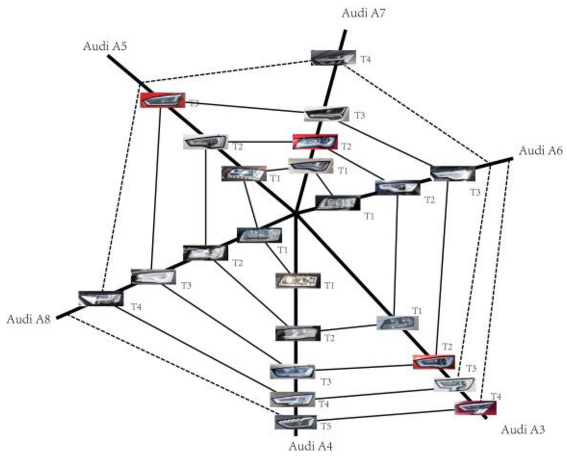


Figure 3: Product family described by a spider-web structure.

2.2 Product Kansei Image Cognition and Spider-web Mechanical Properties

Cognition is a continuous process through which human beings constantly perceive the world. The continuous convergence of new and old cognition is a manifestation of multiple extensions of cognitive content [23]. The kansei image, which represents a person's emotional cognition, is a human brain response triggered by external stimuli. As a kind of psychological activity, the product kansei image refers to the association of users with the product through their own senses, which is called "Kansei" in Japanese [24].

In the research of kansei image-driven product form design, consumers' kansei image demands for products are complex and extensive, especially for multi-image products that satisfy specific consumer groups and values [14]. For a product family, external factors that influence the product iteration process, such as technology, the environment, and the humanities, are similar to prey that hit a spider-web. In the initial stage, there is equilibrium. When external factors change, like prey hitting a spider-web, the balance is broken, which will promote the deformation of the spider-web structure and produce an energy exchange. The radial silk and capture silk in the spider-web will consume most of the energy [25]. When external factors change, enterprises will be prompted to iterate their products to quickly respond to market demands and meet consumer kansei image requirements. In this rapid iteration, the kansei image of the product will also change slightly, and each product series will have multiple kansei images [26]. For example, Xue established qualitative and quantitative decision-making models of product kansei image design through Kansei Engineering experiments, predicted the overall product kansei image, and finally obtained a multi-image [27]. This kansei image change law and the driving relationship between kansei image and product form are similar to the mechanical properties of radial silk and capture silk in a spider-web.

Firstly, consumers' kansei image demands change over time. The change of a product kansei image creates a nonlinear curve, as shown in Figure 4. This is similar to the mechanical properties of spider silk. Through experiments and simulations, Steven found that the superiority of spider silk is manifested in its nonlinear mechanical properties and geometric arrangement structure [28]. Spider silk is a typical viscoelastic body that experiences creep under force [29]. The nonlinear curve of spider silk's mechanical response is shown in Figure 5 [30], and its change law is similar to the nonlinear change phenomenon of product form over time.

Secondly, the product form is driven by multiple kansei images. The designer mainly inherits the characteristics of the previous generation of products according to kansei image demands and also learns from the design features of other kansei image series. Each design feature is a carrier of kansei image expression. The new product is influenced by the driving mode of the same series kansei image as the main kansei image and the other series kansei image as the reverse kansei image, forming the compound kansei image product form. This process is similar to the mechanical properties of radial silk and capture silk. Radial silk and capture silk are composed of different proteins. The radial silk that constructs the supporting frame of web is stiff as strong as steel, while the capture silk is much weaker but more than ten times as extensible [31]. The micro structures of these two types of silk are different, as are their force changes [32]. Radial silk has a higher strength, modulus, and toughness than capture silk, and its mechanical law is similar to the design law of kansei image attenuation within a single product series, while the rapid attenuation of the force on the capture silk conforms to the weak kansei image influence between product series.

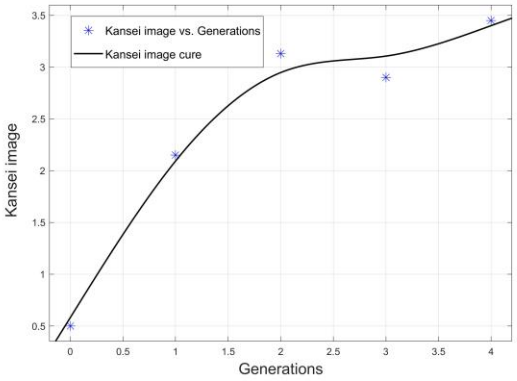


Figure 4: Product kansei image change curve.

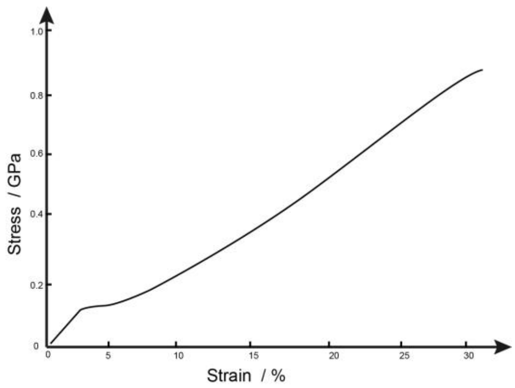


Figure 5: Curve of spider silk stress.

In summary, the product family tree generated by the strategic layout of enterprise product research and development is similar to a spider-web at both the macro and micro levels. In the process of product upgrading, there are inheritances and innovations in the product forms between generations of products in the same series, and there are also references to product forms between series. This relationship is similar to the connection between radial silk and capture silk in the spider-webs. However, the existing product genealogical chart is essentially a product family tree, such as the Leica camera family tree, which strengthens the dynamic evolution design of product series iteration while ignoring the interactions between the series. For the relationship in product serialization design, we previously performed preliminary explorations [33], but there has been no further research on the quantitative relationship between the nonlinear characteristics of spider-web mechanics and product form. Based on the existing research, this paper uses the nonlinear characteristics of spider-web mechanics to study the inheritance and innovation between generations of the same series of products and the product form reference relationship between series. Characterizing this relationship with a spider-web structure will provide a new path for studying the serialization development of products.

3 PRODUCT FORM SPIDER-WEB EVOLUTION MODEL BASED ON SPIDER-WEB

By analyzing the similarities between product serialization and spider-web structure at micro and macro levels, the research process is established. And it includes two parts: product kansei image spider-web model and product form spider-web evolution model. Based on the above models, we constructed algorithm program and human-computer interaction interface to assist product designers in new product development. Firstly, through the website, the product pictures and kansei image words of product series are collected. According to the product pictures and kansei image words, a kansei image survey is carried out to obtain the kansei image evaluation data. The data was analyzed to obtain the qualitative order of kansei image through cluster analysis. Secondly, based on the information entropy theory, the weight of each kansei image is calculated and transformed into an angle of spider-web. Combined with the macro structure of spider-web, the product kansei image spider-web model is constructed. Next, based on the mechanical law of spider silk and the inheritance of product kansei image, the transfer expressions of product kansei image in radial silk and capture silk are proposed through the related parameters of previous generation of products. The two expressions are introduced into genetic algorithm as crossover and variation coefficients to construct the product form spider-web evolution model. Then, based on the above models, we develop an algorithm program and human-computer interface. Finally, the research method is illustrated by the product case of Audi A series car headlight.

3.1 Product Kansei Image Spider-web Model

3.1.1 Building kansei image matrix

We collected the product pictures and image words from product websites, extracted the contour feature lines of the product shape, and designed a semantic differential (SD) questionnaire to conduct image evaluation surveys. It is assumed that there are *n* product series (image), *m* samples. And the *j*-th image value of the *i*-th sample is H_{ij}. Product image matrix A_H is defined according to the survey data.

$$A_H = \left[H_{ij}\right] = \begin{bmatrix} H_{11} & H_{12} & \cdots & H_{1n} \\ H_{21} & H_{22} & \cdots & H_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ H_{m1} & H_{m2} & \cdots & H_{mn} \end{bmatrix} \tag{1}$$

According to the product kansei image positioning on the official website, the kansei image word is used as the main kansei image of this series, while the other kansei image words are the secondary images [33].

3.1.2 Kansei image ordering

3.1.2.1 Kansei image clustering

We cluster and sort kansei image words according to the distance between them.

3.1.2.2 Weight calculation of the kansei image region

To reduce the errors, the kansei image matrix A_H is normalized to obtain the decision matrix A_Y:

$$A_Y = \left[y_{ij}\right] \tag{2}$$

Then, we get the probability P_{ij} of the target kansei image as follows:

$$P_{ij} = \frac{y_{ij}}{\sum_{i=1}^{m} y_{ij}} \tag{3}$$

where y_{ij} represents the normalized value of the *j*-th target kansei image evaluation of the *i*-th sample.

After ordering kansei images, it is necessary to quantify the proportion of each kansei image in constructing the product kansei image spider-web model. The information entropy proposed by the American engineer Claude Elwood Shannon is used to measure the negative entropy of the information. Su introduced the use of information entropy to calculate the kansei image entropy of each kansei image [34]. The formula is as follows:

$$I_j = -k\sum_{i=1}^{m} P_{ij} \ln P_{ij} \tag{4}$$

where I_i represents the kansei image entropy value, P_{ij} is the probability of the j-th kansei image of the i-th sample, $0 < P_{ij} < 1$, k is a constant, and $k = 1/\ln m$. The obtained target kansei image probability P_{ij} is then taken into the kansei image entropy Equation (4).

This paper use information entropy to quantitatively analyze the kansei image cognition in product form design and quantify the proportion of each kansei image in the product kansei image spider-web.

Then, the weight W_j of the target kansei image in the evaluation process is as follows:

$$W_j = \frac{1-I_j}{\sum_{j=1}^{m}(1-I_j)} \tag{5}$$

The weight of each kansei image is obtained to construct the product kansei image spider-web model for the next step.

3.1.3 Building a product kansei image spider-web model

(1) k-means clustering analysis is used to analyze the n kansei image words according to the experimental data. Each word is a cluster center, and the distance between the word and other words can be obtained. By selecting a word as the target kansei image positioning word, the distances between that word and the other words are compared to arrange them from near to far to obtain the order of the kansei image words.

(2) According to Equations (1)–(5), the weight of the j-th kansei image is W_j, and the kansei image weight matrix W_j is obtained as follows:

$$W_j = \left[w_1, w_2, \ldots w_k \ldots, w_n\right] \tag{6}$$

(3) The angle weight matrix V_j is obtained according to the kansei image weight W_j :

$$V_j = \left[v_1, v_2, \ldots, v_k, \ldots, v_n\right] \tag{7}$$

The angle weight calculation equation is as follows:

$$V_k = \frac{w_k}{\min W_j} \tag{8}$$

(4) According to Equation (9), the angle weights are converted into angle values. The area of each kansei image is shown in Figure 6.

$$\alpha_k = \frac{360 * V_k}{\sum_{b=1}^{n} V_b} \tag{9}$$

To express the kansei image clearly, the bisector of each kansei image angle is defined as the kansei image to establish a product kansei image spider-web model, as shown in Figure 7. In this model, the kansei image value of the area far away from the kansei image line is weak. The kansei image value decreases along the direction of the red arrows.

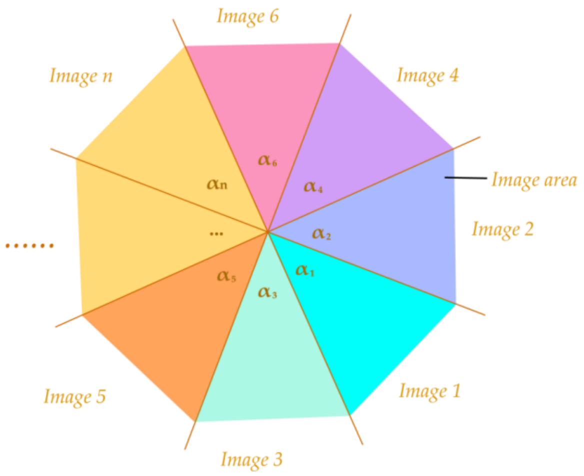


Figure 6: Kansei image areas.

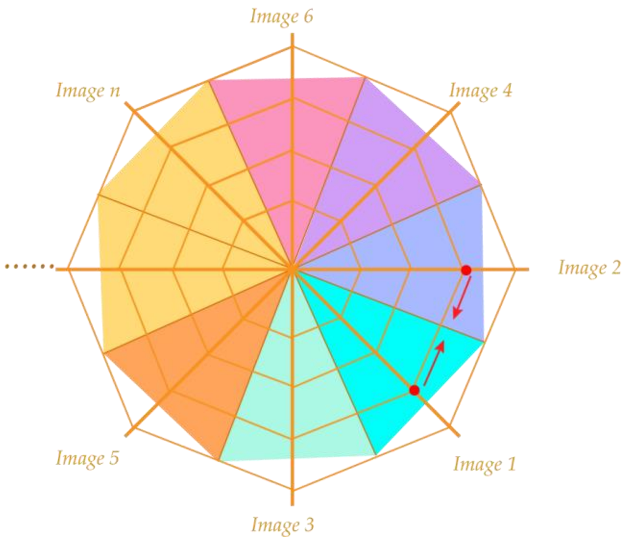


Figure 7: Product kansei image spider-web model.

3.2 Spider-web Evolution Parameters for Product Form

3.2.1 Intergenerational variation

Kansei image variation was defined as the form difference degree between two generations of products. The smaller the similarity between the product forms is, the greater the degree of form difference is, and the greater the kansei image variation is. The equation to calculate the kansei image variation ($\triangle L_m$) is as follows [35]:

$$\Delta L_m = 1 - q_{p_i p_j} = \sum_{i=1}^{x} \frac{0.5 + 0.5 \cdot \cos\theta}{\left| R_{p_{ik} p_{jk}} - 1 \right| + 1} \Big/ x \tag{10}$$

$$\cos\theta = \frac{p_{ik} \cdot p_{jk}}{\sqrt{p_{ik}^{2}} \cdot \sqrt{p_{jk}^{2}}} \tag{11}$$

$$R_{p_{ik} p_{jk}} = \frac{|p_{ik}|}{|p_{jk}|} = \frac{\sqrt{p_{ik}^{2}}}{\sqrt{p_{jk}^{2}}} \tag{12}$$

where $q_{p_i p_j}$ is the similarity between product forms, θ represents the angle between the two vectors P_{ik} and P_{jk}, and $R_{P_{ik}P_{jk}}$ is the modulus ratio of the corresponding vectors P_{ik} and P_{jk}. P_i is the vector set composed of the key points of the *i*-th form, which can be described as $P_i = (p_{i1}, p_{i2}, \cdots, p_{ik}, \cdots, p_{ix})^T$.

3.2.2 Parameters

R is defined as the impact of external information on the spider-web of the product kansei image. The greater the *R* value is, the greater the impact of external information is. Moreover, the greater the variation coefficient is, and the greater the product form change is. Because information cannot be quantified and predicted, it is set as a random function from 0 to 1.

The relationships between ρ, α, l_m, $l^c{}_m$, $\triangle L^{A}{}_{1m}$, $\triangle L^{B}{}_{1m}$, and $\triangle L^{C}{}_{1m}$ are shown in Figure 8 and can be organized with the following equations:

$$\theta_1 = \frac{\alpha_A}{2} + \frac{\alpha_B}{2} \tag{13}$$

$$\theta_2 = \frac{\alpha_A}{2} + \frac{\alpha_C}{2} \tag{14}$$

$$\rho_1 = \sqrt{1 - \frac{\sin\theta_1^{\,2} * \Delta \mathrm{L}^{\mathrm{B}}{}_{1\mathrm{m}}{}^{2}}{\Delta l^{B}{}_{m}{}^{2}}} \tag{15}$$

$$\rho_2 = \sqrt{1 - \frac{\sin\theta_2^{\,2} * \Delta \mathrm{L}^{\mathrm{C}}{}_{1\mathrm{m}}{}^{2}}{\Delta l^{C}{}_{m}{}^{2}}} \tag{16}$$

$$l_m = \sqrt{\Delta L^{B}{}_{1m}{}^{2} + \Delta L^{A}{}_{1m}{}^{2} - 2 * \Delta L^{B}{}_{1m} * \Delta L^{A}{}_{1m} * \cos\theta_1} \tag{17}$$

$$l^{C}{}_{m} = \sqrt{\Delta L^{C}{}_{1m}{}^{2} + \Delta L^{A}{}_{1m}{}^{2} - 2 * \Delta L^{C}{}_{1m} * \Delta L^{A}{}_{1m} * \cos\theta_2} \tag{18}$$

3.2.3 Mathematical model of kansei image driving

The research from [25], [36,37] related to spider-web and spider silk mechanics is next applied to analyze the development of the product series. In this way, we quantify the kansei image interactions between products in the same series and different series to characterize the driving effects of the kansei image on the product form.

By combining the characteristics of design thinking that diverges first and then converges [38], the form that first affects the designer's design thinking will determine the degree of innovation in the new form. The closer the kansei image series is to the target kansei image, the greater the impact on product form innovation will be.

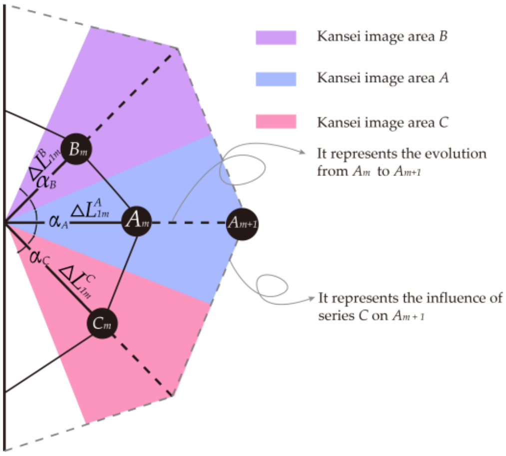


Figure 8: The relationship between the parent and offspring in the product family.

Therefore, a product's morphological variation is mainly formed by the combined influence of the target kansei image series and the kansei image series closest to the target kansei image. Then, good features are borrowed from the more distant kansei image series to complete the product's morphological innovation. Here, the collateral kansei image change closest to the target kansei image series is combined with the target kansei image change to form the kansei image radial line equation, where the more distant kansei image series influence the target kansei image series to form the capture line equation.

The transmission of a product kansei image in the radial direction can be expressed as

$$\Delta L_{m+1} = \frac{R_{m+1}}{\left(\frac{\Delta L_m}{L_m} + \rho_1{}^2 * \frac{\Delta L^A{}_{1m}}{l^B{}_m}\right) * H} \tag{19}$$

where R_{m+1} represents the impact of external information on the radial line. Since the impact of external information on the product form cannot be accurately quantified, a random function is set to simulate the impact of external information on the radial line:

$\triangle L_{m+1}$ represents the variation of kansei image A in the m+1-th generation;

L_m represents the time interval between the m-th generation and the m+1-th generation of the kansei image A;

$\triangle L_m$ represents the variation of kansei image A from the $m-1$-th generation to the m-th generation;

$\triangle L^A{}_{1m}$ represents the variation of kansei image A from the first generation to the m-th generation;

$l^B{}_m$ represents the kansei image distance between the parent generations of the series B;

ρ_1 represents the relationship parameters between the radial lines and capture lines of the kansei images A and B;

H is a constant, $H = 1$.

The transmission of the product kansei image in the capture line direction can be expressed as

$$\Delta l_{m+1} = \frac{r_{m+1}}{\rho_2 * \frac{\Delta L^{A}{}_{1m}}{l_m^C} * h} \tag{20}$$

where r_{m+1} represents the impact of external information on the capture line;

$\triangle l_{m+1}$ represents the influence of kansei image C on the target series in the m+1-th generation;

$\triangle L^{A}{}_{1m}$ represents the variation of kansei image A from the first generation to the m-th generation;

$L^{C}{}_{m}$ represents the kansei image distance between the kansei image series A and C;

ρ_2 represents the relationship parameters between the radial lines and capture lines of the kansei images A and C;

h is a constant, h = 1.

3.2.4 Solve the evolution coefficient

According to Equations (10)–(13), (15), (17), and (19), $\triangle L_{m+1}$ is calculated to obtain the kansei image variation of the m+1-th generation of the target kansei image in the iteration. The greater the variation is, the greater the intergenerational difference of product form will be. According to Equations (10)–(12), (14), (16), (18), and (20), the $\triangle l_m$ is calculated to obtain the influence of an adjacent series on the target series in the iterative process from the m-th generation to the m+1-th generation. The greater the influence is, the great the crossover will be, and the more the target series will borrow from the adjacent series.

3.3 Product Form Spider-web Evolution Model

3.3.1 Evolutionary design process

- Step 1: The contours of the samples collected in the early stage are extracted and parameterized.
- Step 2: In the time dimension, the product kansei image spider-web is divided along the radial line direction according to the equidistant series. According to the existing iterative relationship, the samples are arranged in the spider-web to construct a spider-web of the product form.
- Step 3: The product kansei image distance L_m of the target kansei image series is calculated through the existing intergenerational relationship. The angle α is calculated according to the kansei image matrix, and the relevant parameters of the radial and capture lines are also calculated.
- Step 4: The kansei image distance is input into Equation (13) to obtain the kansei image variation $\triangle L_{m+1}$ from the m-th generation to the m+1-th generation. Equation (14) is used to obtain the influence $\triangle l_{m+1}$ of the m-th generation of adjacent series on the m+1-th generation of the target series.
- Step 5: $\triangle L_{m+1}$ and $\triangle l_{m+1}$ are combined with the variation and crossover coefficients of the GA, respectively. Genetic operations are carried out to obtain new product forms, and the fitness function is used to evaluate the product forms.
- Step 6: If the conditions are met, the m+1-th generation product form is output; otherwise, return to step 5.
- Step 7: If it is necessary to obtain the m+2-th generation, return to step 4.

3.3.2 Fitness Mechanism

A product sample base was ultimately established, and the kansei image vocabularies were selected. Samples were selected for the questionnaire survey to obtain the kansei image values of each product. The coordinates of key points on the sample contour were also recorded. Taking the coordinates as the input and the kansei image value as the output, a BP neural network was trained. The trained neural network was used as the fitness function of the GA to evaluate the kansei image values of the new products.

4 CASE STUDY

With the development of science and technology, consumers' pursuit of beauty is constantly increasing. In the automotive industry, the headlight form is a crucial design detail, and the outer contour of the headlights form is the most important and recognizable element [39,40]. And compared with other elements, the design of headlights is less restricted. Therefore, we choose the outer contour of car headlights as an example.

Using the product form spider-web evolution model outlined in section 3, this section takes the Audi A series car headlights as an example to describe the detailed steps of the model and verify its feasibility.

4.1 Kansei Image Experiment

4.1.1 Design and implementation of experiments

We took the outlines of the Audi A3-A8 series car headlights as the experimental samples and six words as the target kansei images. Then, the experimental objects were determined according to the characteristics of the samples. Finally, we designed a questionnaire for the objects.

(1) Research samples

Through network and market research, 50 headlight pictures of Audi A3–A8 series cars were selected. All the pictures were taken from a side angle of 45° in parallel and included all the products of the A3–A8 series. Through analysis, 23 representative pictures were selected as the primary samples, and their outer contours were extracted. This process is shown in Figure 9.

Figure 9: Feature contour extraction.

(2) Target kansei image words

From the official website of Audi, six representative kansei image words were selected by the expert analysis method: "Penetrating", "Aggressive", "Sporty", "Noble", "Elegant", and

"Technology". These six words successively correspond to the Audi A3–A8 series and comprised the target kansei image vocabulary.

(3) Experimental subjects

The experimental study involved forty subjects, including fifteen consumers, fifteen designers, five car salespeople, and five car-related engineers.

(4) Designing the questionnaire

Twenty-three research samples and six kansei image words were used to establish a five-level SD questionnaire, as shown in Figure 10.

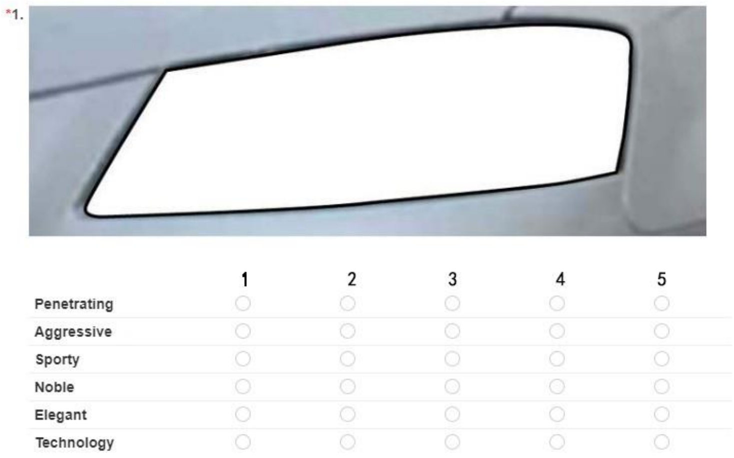


Figure 10: SD questionnaire (in the actual experiment, the questionnaire content was in Chinese).

4.1.2 Experimental data statistics

Forty questionnaires were distributed throughout the survey, and forty valid questionnaires were collected. Using data statistics, a kansei image matrix A_H of the headlight contours of Audi A series cars was constructed. The kansei image value datum is the average of the items in all questionnaires. A_H is as follows:

$$A_H = \begin{bmatrix} 2.90 & 2.80 & 2.48 & 2.53 & 2.55 & 2.58 \\ 2.38 & 2.15 & 2.45 & 2.90 & 2.95 & 2.5 \\ 2.50 & 2.38 & 2.65 & 2.95 & 2.95 & 2.63 \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ 3.63 & 3.18 & 3.6 & 3.08 & 3.73 & 3.48 \end{bmatrix}$$

4.2 Construction of the Product Kansei Image Spider-web Model

"Elegant" was selected as the target kansei image. We carried out a k-means cluster analysis on the data in matrix A_H to calculate the distances between the target kansei image and other kansei images and then sorted the kansei image words according to these distances. The distances between the kansei image words are shown in Table 1.

Cluster	*Penetrating*	*Aggressive*	*Sporty*	*Noble*	*Elegant*	*Technology*
Penetrating		0.730	1.511	2.014	2.185	1.359
Aggressive	0.730		1.192	1.811	1.977	1.043
Sporty	1.511	1.192		1.505	1.550	0.736
Noble	2.014	1.811	1.505		0.631	1.435
Elegant	2.185	1.977	1.550	0.631		1.572
Technology	1.359	1.043	0.736	1.435	1.572	

Table 1: The distances between the kansei image words.

According to Table 1, the distances between “Elegant” and “Penetrating”, “Aggressive”, “Sporty”, “Noble”, and “Technology” are 2.185, 1.977, 1.550, 0.631, and 1.572. Taking "Elegant" as the target kansei image, all kansei image words were ordered according to their distances, as shown in Table 2.

Kansei image	*Penetrating*	*Aggressive*	*Sporty*	*Noble*	*Elegant*	*Technology*
Distance	2.185	1.977	1.550	0.631	0	1.572
Order	6	5	3	2	1	4

Table 2: Kansei image ranking taking "Elegant" as the target kansei image.

By analyzing the table 2, the image words could be arranged in a circle around the target image word in the plane, as shown in Figure 11. Finally, an ordering schematic diagram of the cobweb image words was obtained.

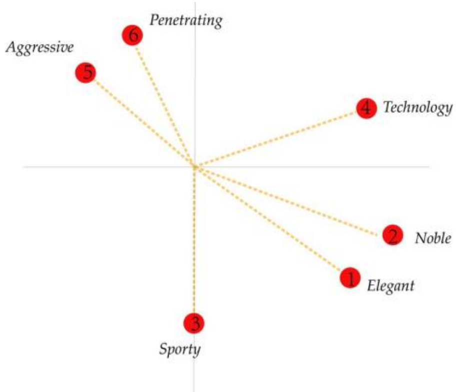


Figure 11: Ordering schematic diagram of the spider-web kansei image words.

According to the kansei image word ordering, the structure of matrix A_H was adjusted, and the data were normalized to obtain the decision matrix A_Y, as follows:

$$A_Y = \begin{bmatrix} 0.0241 & 0.1294 & 0.0262 & 0.0618 & 0.3984 & 0.3536 \\ 0.4659 & 0.4438 & 0.0020 & 0.0020 & 0.0020 & 0.0020 \\ 0.4659 & 0.4863 & 0.1636 & 0.0992 & 0.1423 & 0.0831 \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ . & . & . & . & . & . \\ 0.7199 & 0.5967 & 0.9313 & 0.7344 & 0.9655 & 0.8472 \end{bmatrix}$$

The kansei image probability P_{ij} was calculated using Equation (3). Through Equation (4), we obtained the kansei image entropy value I_j of the j-th kansei image in the A_H, as shown in Table 3.

Kansei image	*Elegant*	*Noble*	*Sporty*	*Technology*	*Aggressive*	*Penetrating*
entropy	0.9515	0.9700	0.9240	0.9268	0.9609	0.9387

Table 3: Kansei image entropy.

According to Equation (5), the kansei image weight matrix W_j was obtained, as shown in Table 4.

Kansei image	*Elegant*	*Noble*	*Sporty*	*Technology*	*Aggressive*	*Penetrating*
weight	0.1478	0.0913	0.2317	0.2230	0.1193	0.1868

Table 4: Kansei image weight matrix.

According to Equation (8) and matrix W_j, the kansei image angle weight matrix V_j was calculated, and the kansei image angle value a_k was obtained according to Equation (9), as shown in Table 5.

Kansei image	*Elegant*	*Noble*	*Sporty*	*Technology*	*Aggressive*	*Penetrating*
a_k	53.22°	32.88°	83.40°	80.28°	42.96°	67.26°

Table 5: Kansei image angle value.

The proportion of each kansei image in the product kansei image spider-web model was then quantified, as shown in Figure 12. To describe the kansei image, the angle bisector of each kansei image angle was defined as the kansei image, and the product kansei image spider-web model was established as shown in Figure 13.

4.3 Parametric Contour

Since the outer contours of car headlights are two symmetrical closed figures, we only chose one headlight as the research object. We then decomposed the outer contours of the sample forms and quantified the contours with the coordinates of 15 key points, as shown in Figure 14.

4.4 Product Form Evolution Model Based on the Mechanical Properties of Spider-web

On the radial line, we segmented the product kansei image spider-web model from the time dimension by taking one year as the unit length. The A7 series headlight outlines and the time series nodes are shown in Figure 15. The T represents the product generation, and the 2003, 2008, 2013, 2018, 2023 are the actual year.

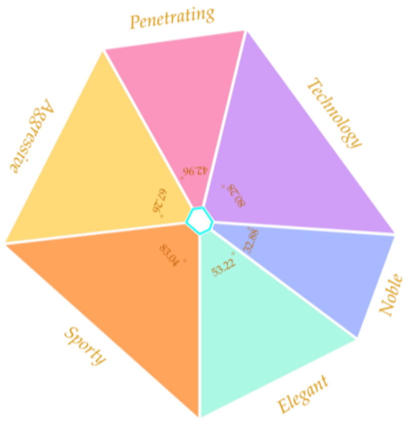


Figure 12: Proportion of each kansei image in the product kansei image spider-web model.

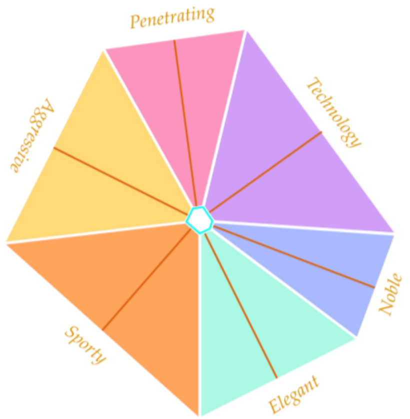


Figure 13: Product kansei image spider-web model.

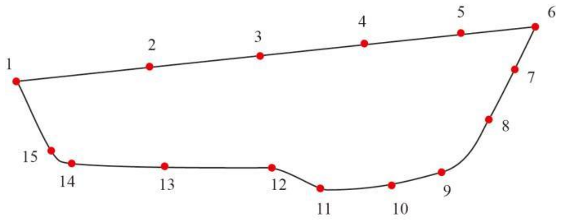


Figure 14: Key points of the car light contour.

We extracted the contours of all samples and arranged them in the product kansei image spider-web model according to the existing iterative relationship in the time series to establish the product form spider-web evolution model. The product prototype (T_0 in Figure 15) is located in the center of the spider-web, and the other products are arranged outward along the radial line, as shown in Figure 16. The intersection of two dashed lines indicates that the series has not yet developed that generation of product.

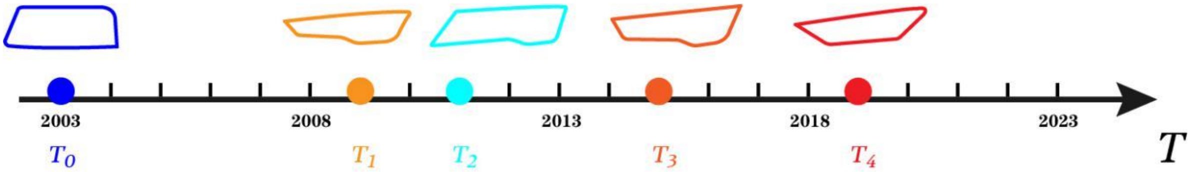


Figure 15: A7 series headlight outlines and time series nodes.

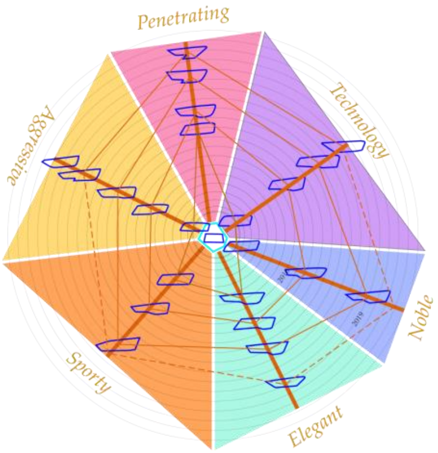
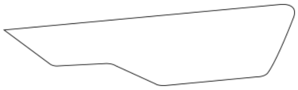


Figure 16: Product form spider-web.

4.4.1 Parent sample parameters

We took "Elegant" as the target kansei image series. Its direct parent is the fourth-generation product form of the A7 series, and its collateral parents are the third-generation product form of the A6 series and the third-generation product form of the A5 series. Their key point parameters are shown in Table 6.

Parent	*The 4th generation of the A7 series*		*The 3rd generation of the A6 series*		*The 3rd generation of the A5 series*	
						
Key points	*X*	*Y*	*X*	*Y*	*X*	*Y*
1	−129.71	2.67	−138.47	14.2	−122.3	−4.54
2	−78.35	10.05	−47.21	22.58	−75.02	10.52
3	−18.47	18.66	47.32	31.27	−31.75	20.16
4	39.58	26.35	125.17	38.42	33.2	28.99

5	116.67	34.89	137.6	26.31	122.3	36.62
6	127.11	22.6	128.8	4.76	114.82	17.06
7	98.95	−4.3	112.95	−26.49	104.07	−11.07
8	78.66	−22.03	103.18	−30.19	97.13	−29.23
9	70.67	−25.08	57.91	−34.45	85.45	−31.15
10	26.89	−28.5	14.99	−38.48	68.44	−33.93
11	16.33	−29.28	5.94	−36.95	19.76	−35.58
12	−4.43	−30.8	−32.4	−19.55	−10.93	−35.87
13	−19.13	−31.87	−40.98	−17.55	−23.99	−36
14	−58.45	−34.73	−86.84	−19.9	−78.55	−36.52
15	−69.51	−32.14	−94.61	−18.14	−99.48	−30.17

Table 6: Key point coordinates of the parent samples.

4.4.2 Kansei image variation

We next extracted the contour parameters of the car lights and constructed a vector matrix. Taking "Elegant" as the target kansei image, the fifth-generation product form of the A7 series evolved based on its fourth-generation product form. Using Equations (10)–(12), we respectively calculated the kansei image variation $\triangle L^7{}_{34}$ between T_3 and T_4 and the kansei image variation $\triangle L^7{}_{04}$ between T_0 and T_3 of the "Elegant" series (A7), as well as the kansei image variation $\triangle L^6{}_{03}$ between T_0 and T_3 of the "Noble" series (A6) and the kansei image variation $\triangle L^5{}_{03}$ between T_0–T_3 of the "Sporty" series (A5). The results are shown in Table 7.

Index	$\triangle L^7{}_{34}$	$\triangle L^7{}_{04}$	$\triangle L^6{}_{03}$	$\triangle L^5{}_{03}$
Vale	0.1787	0.3051	0.2304	0.2254

Table 7: Kansei image variation.

4.4.3 Variation coefficient

Using Equations (13), (15), (17), and (19), the kansei image variation $\triangle L_5$ of the fifth generation of "Elegant" (A7) in the radial line direction was calculated. This variation was combined with the mutation operator of the GA to obtain the variation coefficient.

4.4.4 Crossover coefficient.

Using Equations (14), (16), (18), and (20), the kansei image variation $\triangle l_5$ of the fifth generation of the "Elegant" series (A7) in the capture line direction was calculated. This variation was combined with the crossover operator of the GA to obtain the crossover coefficient.

Index	Parameters	
	$\triangle L_5$	$\triangle l_5$
Vale	0.174	0.705

Table 8: Evolution coefficient on capture line direction.

4.4.5 Performing the GA operations

Taking the Audi A7's fifth-generation headlight form deduction as an example, the time interval parameter from the fourth-generation to fifth-generation is Lm = 4. We combined the crossover coefficient and variation coefficient obtained in the previous step to perform the crossover operation and mutation operation. The evolved product forms were first selected manually and then analyzed using the evaluation system. Finally, the optimal forms that met the kansei image needs were obtained. Based on the above methods, we developed an algorithm program to assist designers. The human–computer interface is shown in Figure 17.

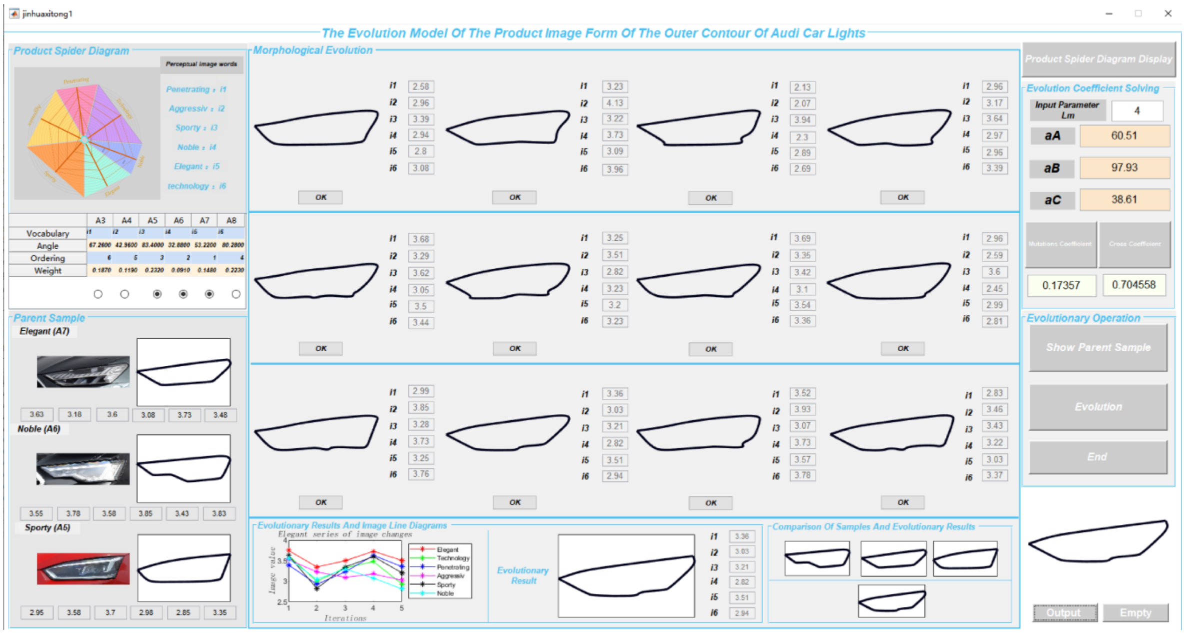


Figure 17: Product form evolution system.

Through a combination of manual selection and a BP neural network, the product forms that meet the kansei image needs were selected out, and the key point coordinates of the optimal product form were output, as shown in Table 9. This system also output the kansei image values of the optimal form, as shown in Table 10. A kansei image change line chart of the "Elegant" (A7) series is shown in Figure 18 under the assumption that the kansei image values of the T_0-generation product form are 2.5. It can be seen in Figure 18 that due to the influence of other kansei image series and external factors, kansei images of the "Elegant" (A7) series changed dynamically and nonlinearly. This provides the basis for quantifying the influence of external factors on kansei images in the time series.

Optimal form	Number of key points	Coordinates	
		X	*Y*
	1	−122.3	−4.54
	2	−78.35	10.05
	3	−18.47	18.66
	4	39.58	26.35
	5	122.3	36.62
	6	127.11	22.66
	7	98.95	−4.31
	8	78.66	−22.03
	9	70.67	−25.08
	10	26.89	−28.5
	11	19.76	−35.58
	12	−10.93	−35.87
	13	−23.99	−36
	14	−58.45	−34.73
	15	−69.51	−32.14

Table 9: Coordinates of the optimal form.

Optimal form	*Penetrating*	*Aggressive*	*Sporty*	*Noble*	*Elegant*	*Technology*
	3.36	3.03	3.21	2.82	3.51	2.94

Table 10: Kansei mage values of the optimal form.

Through an analysis of the product form obtained by evolution, we found that the new product form inherited the characteristics of the direct parent while absorbing some characteristics of the collateral parents. This process is consistent with the characteristics of design thinking in maintaining the main style and learning from the style of similar products. This proves that the product form evolution system with spider-web architecture can effectively simulate the iterative process of product form.

5 DISCUSSION

This paper used the exterior contour design of Audi A series car headlights as a research case, explored the borrowing laws of kansei image and form between product series along with the continuation law of interior series in product family development, simulated design thinking, and realized the prediction of a new product form. We found that the processes of serialization development and the evolution of product forms in a product family are highly similar to the special structures and mechanical properties of spider-webs in nature. In this paper, the spider-web-related research results were used to analyze the development law of product form in a product family, and then the method of obtaining the crossover coefficient and variation coefficient (in the genetic algorithm) for product form evolution was proposed, thereby making the source of the crossover coefficient and variation coefficient more scientific. The product kansei image spider-web model and the product form spider-web evolution model were constructed to predict the new product form and explore the laws of human cognitive change.

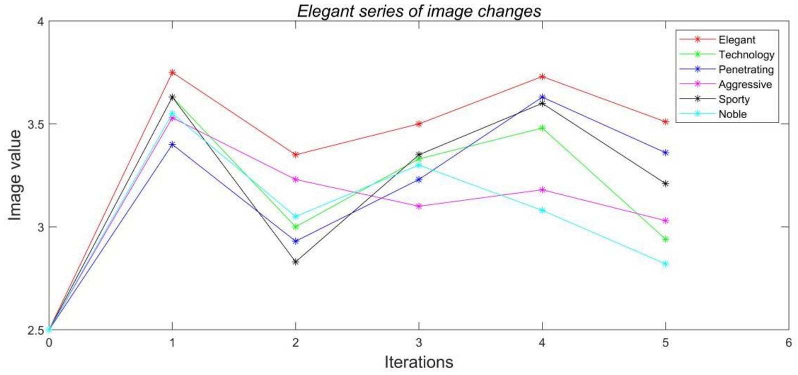


Figure 18: Kansei image iteration of the "Elegant" (A7) series.

External factors, such as users' perceptual cognition, are constantly changing. Technology is developing rapidly. So, changes from decision-makers and other external factors cannot be accurately quantified. Products are composed of multiple form elements that have complex coupling characteristics between them [41]. These aspects of the problem have an impact on the results. To more clearly explain the research content, we weakened the above aspects of the problem. The next step is to study the influence of external factors on the development of the product family and the complex coupling characteristics between the influence degree and product form elements to solve the above problems.

In addition, in many existing product family cases, due to the short-time development of the enterprise and incomplete product development plans, there are inevitable defects in the product family structures. This will have an impact on complete product form spider-web evolution model research and may also affect the accuracy of the variation coefficient and crossover coefficient.

Finally, the overall design of the car headlight needs to consider the form of the internal elements and the entire car contours. How to introduce new methods to reasonably integrate the interior elements, exterior contour of the headlight and the entire car contours to highlight the target kansei image is the focus of future research. In this regard, we have carried out relevant research and achieved some results [42].

6 CONCLUSIONS

We proposed a product form spider-web evolution model based on the mechanical properties of spider-webs. First, based on existing studies, we analyzed the relationship between product form and kansei image in a product family from the perspective of product family development using Kansei Engineering methods to quantify consumers' kansei demands and study the laws of product family development. Second, based on the law of product family development and spider-web structure, a product kansei image spider-web model was established. Third, based on the spider-web mechanics, we explored the kansei image change laws within the product family and the interaction mechanisms between the kansei image and form. Finally, according to the structure of the GA, a product form spider-web evolution model was constructed based on the mechanical properties of the spider-web. The case study indicates that this model can effectively simulate design thinking in product family development.

We conducted an experimental study on the form design of the headlights of Audi A series cars. The result indicates that this model provides good evolution ability. Designers can thus develop in-depth designs based on evolution results to meet their consumer's perceptual expectations. This model will help solve the problems of style image changes caused by a replacement of designers and decision makers in product development and reduce the impact of human factors on products. Although the outline design of the headlights for Audi A series cars was used as the research case in this paper, the present method is applicable to all product form evolution designs. By simulating the design thinking of the designer in the iterative design of new products, we constructed an evolutionary model similar to the nonlinear structure of a spider-web, which provides a method for the rapid iteration of product form. More importantly, this study provides a beneficial exploration of the evolutionary algorithm.

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