Cognitive Association in Interactive Evolutionary Design Process for Product Styling and Application to SUV Design

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Abstract: In recent years, intelligent design technology that is based on interactive evolutionary algorithms, namely interactive evolutionary design (IED) systems, has received extensive attention in the computer science, design, and other related literature. However, due to the complexity of design problems and the limitation of human cognitive ability, IED faces several challenges in actual design applications. With the aim to address these problems in the IED, this paper deconstructs the IED of the product styling from the perspective of the cognitive association of the users, and proposes a corresponding cognitive intervention method that is based on the association of information. We built databases of the perceptual evaluation results of typical cases and coded profiles of the typical cases, combined with the corresponding interaction process, to improve the efficiency of creating associations between dissimilar information in the early stages of evolution. Besides, in order to simplify the process of creating associations between similar information, this paper proposes a clustering model of similar information based on explicit and implicit distances. The proposed method is then applied to the evolutionary design of an SUV. The experimental results show that the proposed method reduces the initial and total evaluation time. Therefore, the proposed method improves users’ ability to understand the complex design tasks of IED for product styling, optimizing the interactive evaluation process by guiding designers to efficiently create the cognitive association of information, and increases the effectiveness of adopting IED to solve actual design problems about product styling.

Keywords: interactive evolutionary design; cognitive association; intelligent design; explicit and implicit distances

1. Introduction

Interactive evolutionary design (IED) is an intelligent design method premised on interactive evolutionary computation which synthesizes human capacity and machine learning [1]. In IED systems, users often do not need to have knowledge of the domain, and only select a population of individuals that have satisfactorily evolved to meet certain criteria based on their personal preferences, and obtain the optimal solution through iteration [2]. Many consider IED systems to be effective for reducing the threshold of design ability and improving design efficiency. As such, IED has received substantial research attention in the field of intelligent design. However, the complexities of design problems and the limitations of the cognitive ability of users can easily reduce efficiency. For example, there is the problem of cognitive noise in the early stages of evolution, that is, the user does not have a clear cognitive understanding of the design goal, and it is difficult to clearly perceive the specific needs of
the actual problem [3]. Additionally, there could be evaluation fatigue during the evolution process; that is, during the iterative process, the user experiences physical and psychological fatigue due to frequent human–computer interaction [4].

Aiming at the problems of cognitive noise and evaluation fatigue in IED, recent work mainly focuses on improving expression methods of individual fitness, constructing surrogate models, and improving interactive processes. Yang et al. [5] used a trapezoidal fuzzy number to express individual fitness, and calculated individual fuzzy fitness based on user evaluation noise at different stages of evolution, so as to alleviate user noise and improve evolution efficiency. Lv et al. [6] adopted a Gaussian fuzzy number to represent individual fitness, and constructed a surrogate model to replace user evaluation in the evolution process. Leelathakul et al. [7] divided the evolution process into two stages, which includes the evolution of the overall shape and the local feature. Users can initialize or reserve an individual at any time to realize the users’ intervention. In addition, Takenouchi et al. [8] employed a Human Vision Component BST-007001 to collect the gaze information of group users and obtain group preferences. Cascini et al. [9] applied a projection-based AR system to collaborative design, which improved the interaction between designers and design prototypes. These new technology-based methods are meaningful to improve the individual evaluation process, but their effectiveness needs to be verified in practice. In short, the above methods mainly relieve user fatigue by reducing the complexity of the evaluation process, but they less systematically involve the user cognition and solution process of design problems.

In addition, the user cognition is also significant in product styling design. The way that a product is styled (created to provide visual pleasure) involves both perceptual judgment and the aesthetics of the product itself. However, both can be ambiguous and implicit due to subjectivity. Resolving the issues during the product styling process requires cognitive mapping which transforms implicit knowledge into an explicit form. Yet interactive evolutionary computing during a product styling process means that the designers are subjected to cognitive noise and evaluation fatigue which essentially originate from inefficient cognitive association between information in the problem domain and the solutions in the feature domain. For example, in the early stages of evolution, users lack information to associate elements and logical interactive patterns that provide competent relationships, thus causing difficulties for users to create associations between dissimilar information in the problem domain to the generated solutions in the feature domain. In evolutionary iteration, the user evaluation process is accompanied by a considerable number of cognitive association processes of individuals, which require substantial mental resources for cognitive processing and easily cause evaluation fatigue. Therefore, in the traditional IED for product styling, the cognitive process of design tasks and the evaluation process of evolution individuals are complicated and inefficient due to the difficulty of creating cognitive association.

This paper deconstructs the IED process for product styling from the perspective of cognitive association by combining the cognitive characteristics of designers in traditional product styling design. Then, the paper focuses on an IED method of product styling that is characterized by the association of information to stimulate user cognition. In the early stages of evolution, an interaction process is designed to guide users to create the association of dissimilar information by building databases of the perceptual evaluation results of typical cases, and coded profiles of the typical cases. During the evolution process, a multiple linear regression statistical analysis is used to establish an implicit association model between the perceptual evaluation of the typical cases and morphological features for cognitive mapping. Then, a clustering method of the individuals that comprehensively considers the explicit and implicit distances is established to improve the cognitive efficiency of the user fitness evaluation process. Finally, the method is applied in the design process of an SUV to validate the effectiveness of the corresponding cognitive intervention method that is based on the cognitive association.

The contributions in this paper mainly embody in the following three aspects. First, from the perspective of cognitive association, we deconstruct the cognitive process in IED for product styling
into a process of cognitive association between dissimilar information and similar information by combining the cognitive characteristics of product styling design from professional designers. This kind of deconstruction provides a new idea for studying the cognitive process of IED for product styling; second, the proposed mapping model of association of dissimilar information improves users’ ability to understand complex design tasks, and helps to create cognitive association between design tasks and morphological features; third, the proposed clustering strategy of similar information helps the overall perception and the detailed comparison of evolution individuals for users, and reduces the cognitive resources of the evaluation process. These contributions improve the efficiency of creating cognitive association and reduce the consumption of cognitive resources for users, therefore it is beneficial to solve the problems of complex product styling design.

The remaining sections of this paper proceed as follows. Section 2 summarizes the problems with associating information during design activities and those in the IED process. Section 3 provides a detailed introduction to the cognitive intervention methods that are based on the association, including the cognitive mapping strategy of associating dissimilar information and clustering of similar information. Section 4 is a case study that describes the evolutionary design process and use of an SUV profile based on the proposed method, the design and implementation of the experiments, and an analysis and discussion of the results. Section 5 presents the conclusions, limitations, and recommended future research work.

2. Cognitive Association in Interactive Evolutionary Design of Product Styling

Cognition is the process and ability to acquire knowledge and solve problems, or the process of comprehending and managing received information [10,11]. The cognitive association of information is defined as the linking of two or more elements and defining their mutual relationship [12]. Such elements can include both concrete objects and abstract concepts. The relationship between information refers to the correlation among different information elements and is the core element for users to understand information.

The cognitive process of an individual to understand problems is by acquiring knowledge through thinking, experiencing and sensing. This acquisition of knowledge is achieved through learning, which involves experiencing, studying and receiving instructions. Eventually, one learns to form associations in information for problem solving tasks, and gradually develops a cognitive structure. Those who have not yet developed or fully developed their cognitive structure would find it difficult to obtain the solution to a new problem or might obtain an erroneous solution. In order to help designers develop a cognitive structure that contributes to finding the optimal solution of design problems, it is first important to study the problems by associating information during the product styling and the IED processes.

2.1. Association of Information during Product Styling Process

Creating associations with information needs to start right at the beginning of the design activities and be implemented until the end of the design process.

Experienced designers might find that the styling process of a product is somewhat linear [13]. This linear design process constitutes of the acquisition of associated elements, and creation of their relationships. As shown in Figure 1, the main information tasks in a designing activity that require the ability to associate are: the design task, referencing to different cases, drafting the design, and creating the final design scheme. The design task and referencing to different cases are based on the information obtained by the designer, and drafting the design and creating the final design scheme result in newly created information. The relationships that mainly need to be developed in design activities are those between the task information and reference cases, reference elements and morphological characteristics, and the different drafted designs. Among them, the first two relationships involve different elements (i.e., association of dissimilar information) while the latter relationship identifies the same schemes (i.e., association of similar information).
The design task is generally based on text and abstract elements, and is the original starting point of design cognition. The designer uses his/her own experience, preferences and style to interpret the task information in his/her own unique way, and according to the interpretation, retrieves the elements of the associated reference case from memory or other external resources (can be images, videos, webpages, and other mediums), so as to transform the task information which is made up of less obvious and abstract text into relatively clear and graphic images. This cognitive process creates a relationship between the design task and reference case. Then, the designer analogizes the obtained reference case, and refines the morphological characteristics (by using symbols and other mediums to convey the message) to meet the task objectives. This cognitive process involves creating a relationship between reference cases and styling features. Since the design task, reference cases, and styling features involved in the two cognitive processes above contain different kinds of information, the amount of information and the medium are different, so they are dissimilar information. When there are a number of design drafts, designers need to conduct evaluations on both function and aesthetics. They will have to cognitively construct relationships to determine the pros and cons of the design drafts. The type of information, the volume of information, and the medium of expression for design drafts is basically the same, so there are similar relationships.

In short, the association of information in a design activity is always carried out, which includes both the acquisition of associated elements, and creation of their relationships. Efficiency in creating associations of information is an important factor that improves the efficiency of the design task.

2.2. Association of Information in IED Process for Product Styling

IED is an intelligent design method premised on interactive evolutionary computation which synthesizes human capacity and machine learning. It is based on iterative design which is carried out within a predetermined constraint [14]. Computers can effectively understand human intuition, preferences and other perceptual information, and then produce a large number of design solutions that meet the needs, which are widely used in design fields such as graphic patterns [7], clothing [15], products [16], etc.

As shown in Figure 2, the IED for product styling is a different process than conventional styling design processes. The scheme in the IED process is electronically generated by using a computer, and human intervention is mainly to evaluate the schemes, that is, creating the relationships between elements with similar information, and IED is designed without considering the cognitive association of dissimilar information in the early stages of evolution. Therefore, compared to conventional design processes, the IED process mainly involves the association of information for design tasks and drafts, and the development of relationships among similar information.
However, there are two problems in the cognitive association of information in the IED process for product styling.

On the one hand, the understanding of designers of the design task is low due to the lack of reference cases in the early stages of evolutionary design, and the logical process of developing association among dissimilar information. Users can only gradually clarify the design task through an evaluation of the fitness of the individuals, and then map the relationship between the referencing cases and specific morphological features. The lack of reference cases compels users to search for useful elements and scenarios from memory/personal experiences to clarify the relationship between task and feature which in turn increases the cognitive burden and consumes cognitive resources. In addition, the relationship between the design task and specific features is not considered due to the random production of the first-generation schemes, which results in a lack of effective evaluations in the early stages [17]. Therefore, in traditional IED (TIED) systems, the development of the association of dissimilar information has problems including the lack of a logical interaction process that is beneficial to create associations between dissimilar information, lack of reference cases, and the random initialization of the population without considering the cognitive association of users.

On the other hand, during the stage of associating similar information, TIED processes are mainly implemented by electronically generating several evolutionary individuals simultaneously, and users assign the fitness value for each individual. In general, users need to classify and compare the information contained in each individual to carry out a reasonable evaluation. However, interactive assignments that are completed for each individual means that during the evaluation process, the user is only focused on a specific individual, and it is difficult for them to observe the relationship between the pros and cons of all individuals. To address this issue, Tomczyk and Kadzinski [18] adopted a pairwise comparison of individual evaluation methods to facilitate the individual comparison process of the users. Additionally, assigning evaluation values consumes the cognitive resources of users [8] because user preferences are difficult to quantify. In addition, the scheme layout is random and disorderly, which requires users to actively classify the schemes mentally [19]. De Koning et al. [20] pointed out that if the cognitive information to be processed is placed closer, the cognitive efficiency of users is higher. Ayres and Sweller [21] proposed that users will suffer additional cognitive burdens when processing and matching information from split-attention materials. Therefore, it can be seen that the evaluation process and scheme presentation methods of TIED systems are not conducive to the process of creating association between similar information and instead require more cognitive effort thus leading to cognitive consumption.

Therefore, through the overall consideration of the cognitive association of IED for product styling, the methods that should be adopted to improve the efficiency of associating information, so as to reduce cognitive consumption, and improve the quality of evolutionary designs, are worthy of further study.

3. Methods

In view of the above-mentioned problems, this section proposes a cognitive intervention method for the IED of a product shape driven by associated information, which has the two following
parts: mapping of the process of associating dissimilar information; clustering of similar information, constructing a clustering algorithm that comprehensively considers the explicit and implicit distances.

The methodology flow chart is shown in Figure 3. The first stage is the mapping model of associating dissimilar information includes building databases on the perceptual evaluation results of typical cases and the coded profiles of the typical cases and designing the interactive process. The second stage is the clustering of similar information (in this case, profiles), which includes mapping perceptual images and morphological features, and the construction of a clustering algorithm that comprehensively considers the explicit and implicit distances. Finally, there is the basic process of product styling with an IED system.

**Figure 3. Methodology flow chart.**

### 3.1. Mapping of Association of Dissimilar Information in the Early Stages of Evolution

The three following strategies are proposed with the aim to address the three problems: the lack of a logical interaction process that is beneficial to create association, lack of reference cases, and the random initialization of the population without considering the cognitive association of users in cognitive association of dissimilar information in TIED processes, as mentioned in Section 2.2.

Strategy one is to design an interaction process to guide users to create the association of dissimilar information by involving building databases on the perceptual evaluation results of typical cases and the coded profiles of the typical cases to create relationships of association among them. Thus, the implicit association that accompanies the user evaluation process in a TIED process is embodied in the process of interacting, and guiding systematic and logical thinking. Strategy two is the use of a system that provides substantive reference cases to reduce the need to the recall for reference cases. Strategy three is to directly apply satisfactory cases selected by users to produce the initial population of IED systems, and the created cognitive association intervenes in the initialization of the population.
The perceptual image of the design object is expressed as $A = [a_1, a_2, \ldots, a_n]$, where $n$ denotes the evaluation dimension of the perceptual image, and $a_n$ denotes the perceptual image value of the $n^{th}$ dimension. The coded profiles of the typical cases are denoted as $B = [b_1, b_2, \ldots, b_m]$, where $b_m$ denotes a specific reference case, and $m$ is the total number of cases. At present, the commonly used methods of determining perceptual images are the semantic differential [22], and principal component analysis [23] methods. The semantic differential is the most commonly used technique in Kansei Engineering to measure user perception of product styling [24], and it is also a commonly used method to quantify the perceptual image. The principal component analysis method is often used to reduce dimensionality [25]. First, the semantic distance method along with a Likert scale is used to evaluate each case in $B$ based on the dimensions of perceptual image $A$, and the resultant perceptual evaluation matrix is as follows:

$$A \rightarrow B = \begin{bmatrix}
A_{b_1} \\
A_{b_2} \\
\vdots \\
A_{b_m}
\end{bmatrix} =
\begin{bmatrix}
a_{11} & a_{12} & \ldots & a_{1n} \\
a_{21} & a_{22} & \ldots & a_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
a_{m1} & a_{m2} & \ldots & a_{mn}
\end{bmatrix},$$

(1)

Then, the individuals in the typical cases are coded. The coding rules should be the same as those for the individual phenotype in the IED process to construct relationships of association based on reference cases and extended to the first-generation of evolved individuals.

3.2. “Explicit–Implicit” Fused Clustering of Similar Information during Evolution Process

3.2.1. Clustering Ideas

The following strategy is proposed in response to the problem with the evaluation process and scheme layout in the cognitive association of similar information in the TIED system as mentioned in Section 2.2, by constructing a clustering model of similar information, and presenting the evolution individuals in the form of clusters instead of mentally processing similar information.

When users discern morphological similarities, the spatial (geometric) distance between each individual shape is only one of the factors to determine whether they are similar or not. At the same time, there is the cognitive phenomenon of recognizing different individual shapes in similar perceptual images. For example, in the mental cognition of the term “modern”, users could produce shapes that differ greatly between linear and curvilinear geometric shapes. This phenomenon is more prominent in mentally visualizing styled products, which is a much more complex cognitive task. Therefore, the clustering index not only considers the similarities in the spatial distance of the explicit shape representation of the evolved individuals, but also the similarities in the implicit shape representation of the perceptual image.

On the one hand, this clustering model is based on the considerations of the overall user cognition (perceptual image), which helps users to distinguish the differences in preference among clusters, and on the other hand, it helps them to identify the individual differences among the details in each cluster.

3.2.2. “Explicit–Implicit” Fused Distance Calculation Method

For the calculation of the explicit distance between individuals, the design object of this study is the profile of an SUV, and a quadratic Bezier curve is used to construct the shape of the SUV. The explicit features of the shape of the SUV are expressed by the coordinates of the anchor point and the curvature control point of the Bezier curve. The difference in the explicit features between individuals is expressed by the degree of difference in the individual coordinate sets. The Hausdorff distance is used to calculate the distance between point sets [26], which is often used in image matching, such as handwritten digital recognition [27], facial recognition [28], gesture recognition [29], etc. Here, the Hausdorff distance is used to calculate the explicit distance between individual coordinate sets. Assuming any two individuals $x_i$ and $x_j$ in the population, their phenotypes are expressed as coordinate point sets $P_{x_i}$
and $P_{x_i}$, which are the independent variables, and the explicit distance between them is expressed as $\text{dist}_{\text{explicit}}(x_i, x_j)$, which is the dependent variable. Then the following functional relationship can be obtained as

$$\text{dist}_{\text{explicit}}(x_i, x_j) = \text{Hausdorff}(P_{x_i}, P_{x_j}),$$

Next, to calculate the implicit distance based on perceptual images between individuals, we used the database on the perceptual evaluation results of typical cases in Section 3.1, and refined and summarized the shapes of $b_{m_r}$ and obtained the morphological feature $L = \{l_1, l_2, \ldots, l_q\}$, which is the independent variable. The evaluated value of the visually perceived elements $A_{b_m}$ is used as the dependent variable. Using a multiple linear regression analysis, the mapping model of the association from perceptual image to the morphological features of a product is constructed and expressed as

$$A_{b_m} = w_0 + w_1 l_1 + w_2 l_2 + \ldots + w_q l_q,$$  

Based on Equation (3), the perceptual images in the individuals $x_i$ and $x_j$ are calculated as $A_{x_i}$ and $A_{x_j}$, respectively, which are the independent variables. The implicit distance between two individuals is denoted as $\text{dist}_{\text{implicit}}(x_i, x_j)$, which is the dependent variable, and is calculated as

$$\text{dist}_{\text{implicit}}(x_i, x_j) = \sqrt{(A_{x_i} - A_{x_j})^2},$$

Next, the explicit and implicit distances are integrated and clustering of the individuals in the population is performed. The clustering method used is $k$-means++. The steps to constructing this algorithm are as follows.

First, in the clustering process of the $k$-means++ algorithm, it is important to calculate the distance between the individuals in the population and the cluster center point. The total distance $\text{dist}(x_i, c)$ from an individual $x_i$ to a certain cluster center point $c$ can be expressed by using:

$$\text{dist}(x_i, c) = \sqrt{w \times \max_{c_r \in C} \text{dist}_{\text{explicit}}(x_i, c_r)^2 + (1 - w) \times \max_{c_r \in C} \text{dist}_{\text{implicit}}(x_i, c_r)^2},$$

where, $\text{dist}(x_i, c)$ is the dependent variable, $\text{dist}_{\text{explicit}}(x_i, c)$, $\text{dist}_{\text{implicit}}(x_i, c)$, $\text{dist}_{\text{explicit}}(x_i, c_r)$, $\text{dist}_{\text{implicit}}(x_i, c_r)$, and $w(0 \leq w \leq 1)$ are independent variables, $w$ is the weight of the explicit distance, which is manually set according to the requirements during the evolution process, $C = \{c_r | r = 1, 2, \ldots, k\}$ represents the set of cluster center points, and $k$ is the preset number of classes.

### 3.2.3. Advanced Clustering Algorithm Process

Based on the calculated total distance, the clustering process is as follows.

Step 1: An individual is randomly selected from the population as the initial cluster center $c_1$.

Step 2: Equation (5) is used to calculate the local shortest distance from each individual to the current cluster center, which is denoted as $D(x_i)$. Since the obtained total distance $D(x_i)$ is a relative distance, it cannot be used for direct comparison purposes. Therefore, after obtaining the cluster center $c_{\text{closest}}(x_i)$ that is the closest to each individual $x_i$, the explicit and implicit distances from each individual to the closest cluster center are calculated, and the maximum explicit distance $\max_{x \in X} \text{dist}_{\text{explicit}}(x, c_{\text{closest}}(x))$ and maximum implicit distance $\max_{x \in X} \text{dist}_{\text{implicit}}(x, c_{\text{closest}}(x))$ are determined. Assume that the global smallest distance from the individuals to the cluster center can be denoted as $D(x_i)'$, which is the dependent variable, and $\text{dist}_{\text{explicit}}(x_i, c_{\text{closest}}(x_i))$, $\text{dist}_{\text{implicit}}(x_i, c_{\text{closest}}(x_i))$, $\text{dist}_{\text{explicit}}(x, c_{\text{closest}}(x))$, $\text{dist}_{\text{implicit}}(x, c_{\text{closest}}(x))$. 

dist\text{\textit{implicit}}(x, c_{\text{closest}}(x))$, and $w(0 \leq w \leq 1)$ are independent variables. Then the functional relationship can be obtained as

$$
D(x_i) = \sqrt{wx \frac{\text{dist}_{\text{\textit{explicit}}}(x_i, c_{\text{closest}}(x_i))^2}{\max_{x \in X} \text{dist}_{\text{\textit{explicit}}}(x, c_{\text{closest}}(x))^2} + (1 - w) \frac{\text{dist}_{\text{\textit{implicit}}}(x_i, c_{\text{closest}}(x_i))^2}{\max_{x \in X} \text{dist}_{\text{\textit{implicit}}}(x, c_{\text{closest}}(x))^2}},
$$

(6)

and the probability of the individual being selected as the next cluster center point is denoted as $\frac{D(x_i)^2}{\sum_{x \in X} D(x)^2}$; Then, a roulette wheel approach is used to select the next cluster center point;

Step 3: Step 2 is repeated until $k$ cluster centers are selected;

Step 4: Based on Equation (5), the total distance from each individual $x_i$ to the $k$ cluster centers is calculated, which is classified into the cluster that corresponds to the cluster center point with the smallest distance;

Step 5: The cluster center of each class is recalculated: $c_r = \frac{1}{|c_r|} \sum_{x \in c_r} x$;

Step 6: Steps 4 and 5 are repeated until the position of the cluster center does not change.

4. Case Application

4.1. Creating Association between Perceptual Images-Typical Case-Styling of SUV

The design object of this study is the profile of an SUV. Fiorineschi et al. [30] proposed that the approximate level of the design prototype affects designers’ creativity. Considering performance and cost comprehensively, the side profile of the SUV is used as the prototype of evolution design. In addition, the side profile of the vehicle can effectively show its overall styling and emotional tone, which has a large impact in research work on styling the design of vehicles [31]. First, 60 white side pictures of different SUV models which are categorized as mid-sized SUVs were obtained from the Autohome website (https://www.autohome.com.cn/beijing). The background details were removed, and grayscale processing was performed to reduce the interference information in the initial cases. A group of three experts with more than 10 years of industrial design experience, who were teachers of the industrial design department of the author’s university, were invited to categorize and screen the initial cases, and finally proposed 32 cases as typical cases.

To construct a database of the perceptual evaluation results of typical cases, descriptive adjectives were taken from Su et al. [32] as descriptors of the perceptual image appearance of the vehicles. Two descriptive adjectives, “sporty” and “stylish”, which are closely related to adjectives that motivate the purchase of SUVs, were selected. Thirty industrial design graduate students of the author’s university were solicited to take part in the case evaluation by asking them in person. Ethics approval for this study was obtained from the University Ethics Committee. Written consent was obtained from all of the students. The students used a five item Likert scale to evaluate the selected 32 typical cases to construct a perceptual evaluation matrix for the SUV samples.

To construct a database of the coded profiles of the typical cases, it is important to numerically describe the typical cases. Luo et al. [33] extracted the key point coordinates of two-dimensional contour lines to digitally describe the shape of the side profile. Wang et al. [34] used the elliptical Fourier method to describe and refine the product appearance. To simplify data extraction, this research focuses on the functional parts of the side profile of the SUV. The quadratic Bezier curve function was used in Rhino 6 software to extract the linear points and control the curved points of the different parts of the SUV, and the coordinate data were derived. Then 15 HPs (linear points) and 11 CPs (curved points) were used to quantitatively describe 32 typical cases (see Figure 4).
Figure 4. Typical coded case.

Next, we followed [33,34], and combined the styling features of an SUV to refine the morphological features that help to show a “sporty” and “stylish” image. These features are divided into the overall, sub-global and local features, and are demonstrated based on the coding coordinates. As shown in Table 1, the overall feature is the overall vehicle aspect ratio \( l_1 \), the sub-global feature is the ratio of the width of the body to that of the roof \( l_2 \), height of the vehicle to that of the front of the vehicle \( l_3 \), and width of the vehicle width to that of the front of the vehicle \( l_4 \), and finally, the local features are the angle of the hood \( l_5 \), and front \( l_6 \) and rear \( l_7 \) windshields.

| Parameter | Description | Calculation Method |
|-----------|-------------|--------------------|
| \( l_1 \) | The ratio of the vertical height from HP5 to HP10 to the horizontal width from HP1 to HP7 | \( l_1 = \frac{\text{HP5}(Y) - \text{HP10}(Y)}{\text{HP7}(X) - \text{HP1}(X)} \) |
| \( l_2 \) | The ratio of the horizontal width from HP3 to HP6 to the horizontal width from HP4 to HP5 | \( l_2 = \frac{\text{HP3}(X) - \text{HP6}(X)}{\text{HP5}(X) - \text{HP4}(X)} \) |
| \( l_3 \) | The ratio of the vertical height from HP5 to HP10 to the vertical height from HP3 to HP10 | \( l_3 = \frac{\text{HP5}(Y) - \text{HP10}(Y)}{\text{HP5}(Y) - \text{HP10}(Y)} \) |
| \( l_4 \) | The ratio of the horizontal width of HP1 to HP7 to the horizontal width of HP1 to HP3 | \( l_4 = \frac{\text{HP1}(X) - \text{HP7}(X)}{\text{HP1}(X) - \text{HP3}(X)} \) |
| \( l_5 \) | \( \cos \angle \text{CP1HP2CP2} \) | \( l_5 = \frac{\text{CP1HP2}^2 + \text{CP2HP2}^2 - \text{CP1CP2}^2}{2\text{CP1HP2}\text{CP2HP2}} \) |
| \( l_6 \) | \( \cos \angle \text{CP2HP3CP3} \) | \( l_6 = \frac{\text{CP2HP3}^2 + \text{CP3HP3}^2 - \text{CP2CP3}^2}{2\text{CP2HP3}\text{CP3HP3}} \) |
| \( l_7 \) | \( \cos \angle \text{CP5HP6CP6} \) | \( l_7 = \frac{\text{CP5HP6}^2 + \text{CP6HP6}^2 - \text{CP5CP6}^2}{2\text{CP5HP6}\text{CP6HP6}} \) |

Using the method described in Section 3.2, the mapped relationship between the perceptual image of “sporty” and morphological features \( L \) is constructed by using a through multiple linear regression analysis, \( a_{\text{sporty}} = 0.437 + 0.212 l_1 + 1.075 l_2 - 1.166 l_3 + 0.063 l_4 + 1.096 l_5 - 0.757 l_6 + 1.024 l_7 \). Similarly, the functional relationship \( a_{\text{stylish}} = 4.816 + 0.453 l_1 - 2.336 l_2 + 0.366 l_3 + 0.389 l_4 + 0.357 l_5 + 4.905 l_6 - 0.125 l_7 \) can be obtained. These functional relationships are used to calculate the implicit distance between the evolved individuals.

4.2. System Construction

To simplify the coding of the chromosomes, we directly coded the 26 coordinate points (15 HPs and 11 CPs) extracted, as shown in Figure 4. Since there are 32 sets of typical case codes obtained above, a five-digit binary number is used to encode each coordinate point \( 2^5 = 32 \), and the individual chromosome length is \( 32 \times 5 = 160 \) bits. The specific rules are shown in Table 2. The coding rules of the chromosome are as follows: first, start from HP0 for the contour line of the SUV, code for each point in
a clockwise direction, and end at HP10. Then, code the points on the waistline in the order from left (HP11) to right (HP14). The relationship between genotype and phenotype is illustrated as follows: Assuming that the first to fifth bits of an individual’s chromosome are “00010”, which are converted to a decimal number as two, then the HP0 coordinate of the individual’s phenotype is equal to that of the typical case of serial number two (the serial numbers of 32 typical cases are 0–31).

| Chromosome Position | 1–5 | 6–10 | 11–15 | 16–20 | 21–25 | 26–30 | ... | 151–155 | 156–160 |
|---------------------|-----|------|-------|-------|-------|-------|-----|--------|--------|
| Coordinate Points   | HP0 | CP0  | HP1   | CP1   | HP2   | CP2   | ... | CP10   | HP14   |

The cognitive intervention method of associating information proposed in this paper can theoretically reduce the consumption of cognitive resources in the evaluation process of individuals, so the evolved population is appropriately increased, and the population size is set to 12. The maximum number of evolved generations is set to 10, the crossover rate is 0.6, and the mutation rate is 0.03. Through conducting preliminary experiments in advance, the value of w that yields the best clustering effect is found to be 0.4. Since the ultimate goal of IED is to obtain a number of satisfactory solutions, but not the globally optimal solution, the termination criteria are as follows: (1) the number of satisfactory schemes obtained by the user is four and (2) the maximum number of evolved generations is reached.

The evolutionary design system of the SUV profile constructed in this paper contains two interactive interfaces, which are the interface for associating different information and the interface for the iterative evolution of the schemes.

Figure 5 shows the development of the association between different information elements which involves a specific interaction process, that is, determining the design goals, selecting reference cases, and producing first-generation solutions. There are three components: Parts A, B and C.

Part A is the perceptual selection area which is based on the needs of the users. The users determine the specific values for the two dimensions of “sporty” and “stylish” as central for case retrieval, and select the semantic distance to control the scope of the image retrieval. Green et al. [35] pointed out that the semantic distance between the “source” and “target” is considered to be a decisive element of the innovativeness of the design analogy, that is, the semantic distance between the reference case and the design target will have an impact on the design result. After that, the user clicks on the “OK” button, and the system will generate several matching reference case images.

Part B is the selection area of the reference case: the user selects no more than three reference cases that coincide with the perceptual image based on his/her own experiences and preferences, and the individuals that correspond to the selected case images will be directly incorporated into the primary evolved population.

Part C is the parameter control area. The crossover and mutation rates are set, and then the user clicks on the “Generate First-Generation Population” button to migrate to the interface for the iterative evolution.

Figure 6 shows the interface for the iterative evolution of the schemes, which mainly comprises five components: Parts A, B, C, D and E.

Part A displays the evolved population and evaluation slider, and is used to show the individuals and category information, and evaluate the individuals. The category information reflects the category to which the individuals belong, and differentiated by three different colored rectangles and internal numbers for the interface items. The range of the evaluation slider is zero to 10, and the default value is one. A higher value means higher user satisfaction with the individual. If the evaluation value is zero, the corresponding individual is removed from the population.
Figure 5. Creating interface to associate dissimilar information: (a) Part A, (b) Part B, and (c) Part C.

Figure 6. Interface for iterative evolution of schemes: (a) Part A, (b) Part B, (c) Part C, (d) Part D and (e) Part E.
Part B contains the reference case image, where the reference case images that are finally determined by the user are displayed here for his/her subsequent reference and evaluation, and allows reduction in the amount of information recall when the user cognitively processes the associated information.

Part C contains the optimal individual of the previous generation, which can prompt its use, and is therefore convenient for users in considering the evaluation results of the previous generation. It is also when an optimal solution of the previous generation fully meets the needs of the user, and the user clicks “Join Pool of Schemes”, that is, the solution can be transferred to the satisfactory pool of solutions as the final solution.

Part D contains the satisfactory pool of schemes and situates the user-approved scheme.

Finally, Part E allows parameter setting and data recording. When the overall satisfaction of the user with the current population is very low, he/she can click on “Initiate” to produce a new population of individuals. The settings of the cross and mutation rates default to the inputted value in the previous interface. The slider in the middle is used to control the weight of the explicit distance and the implicit distance when the individuals are clustered. The data recording area is used to record the number of generations and duration of the evolution.

4.3. Experimental Results and Evaluation

Eight industrial design graduate students from the author’s university (four males and four females between 23 and 26 years old) were invited as subjects by asking them in person to conduct a trial with the evolutionary design of the SUV profile based on five methods, which are: (A) the TIED process, (B) the clustering method based on the Hausdorff distance, (C) “explicit–implicit” fused clustering method, (D) methods in the literature [19], and (E) the method proposed in this paper. To ensure that all the subjects have the same level of experience in SUV styling design, none of the subjects invited were previously majors in automotive design, and none of them belong to the 30 students above. In the TIED method, the subjects directly evaluated the generated individuals, do not use the model to create associations in the early stages of evolution, and do not use any individual clustering strategy in the evaluation process. Only one method was tested at a time, and each experiment was separated by one week to prevent bias from the previous experiment which would affect the experimental results. Before each experiment took place, the subjects learned how to use the system to ensure that the experiment could be performed with user proficiency of the operating system.

In related studies, the evaluation time is often used to determine the difficulty of the evaluation process [36,37]. As such, the initial evaluation time of the users is recorded and the total evaluation time in Table 3 is used to study the performance of each method in facilitating efficiency of similar and dissimilar information.

### Table 3. Time used for first generation and total time used by five methods.

| Subject | Time Used for First Generation | Total Time Used |
|---------|-------------------------------|-----------------|
|         | A    | B    | C    | D    | E    | A    | B    | C    | D    | E    |
| 1       | 39.7 | 40.5 | 32.4 | 21.5 | 22.7 | 233.1| 180.8| 183.7| 195.1| 167.0|
| 2       | 36.5 | 42.8 | 29.8 | 24.8 | 21.2 | 257.7| 227.9| 218.4| 214.8| 201.8|
| 3       | 40.3 | 42.4 | 43.3 | 33.4 | 24.8 | 273.6| 243.1| 221.0| 227.2| 204.8|
| 4       | 46.4 | 43.1 | 43.3 | 37.2 | 25.8 | 266.8| 246.0| 224.5| 234.0| 209.1|
| 5       | 50.0 | 48.1 | 47.8 | 38.8 | 29.5 | 246.4| 220.8| 191.7| 205.7| 175.3|
| 6       | 40.9 | 44.5 | 43.1 | 35.0 | 25.8 | 259.8| 227.5| 210.9| 215.8| 197.5|
| 7       | 37.6 | 42.5 | 43.9 | 34.0 | 22.5 | 238.9| 224.1| 207.3| 210.2| 190.1|
| 8       | 39.1 | 41.2 | 44.4 | 32.7 | 22.9 | 231.4| 220.4| 204.8| 208.6| 191.8|

This study compares the time used for the first generation and the total time of five SUV design systems developed based on five methods, and determines the difference in evaluation times of the same user operating different design systems. A paired-sample T test is suitable for comparing the differences in the results of the same subject after using different methods. Therefore, it was appropriate.
to use a paired T test to compare the five methods to verify the effect of different methods on the same subject.

In IBM SPSS Statistics 26, the time required to evaluate the first generation and the total time of the three methods A, B, and C was compared by using a paired-sample T test. The analysis results are shown in Table 4. For the time required to evaluate the first-generation, the difference between Methods A and B in \( t \) is \(-1.59\), and \( P = 0.16 > 0.05 \). It can be seen that Method B has no significant effect on the time to evaluate the first-generation compared to Method A. Similarly, it can be seen that when Method C is compared to Methods A and B, there is no significant effect on the time used to evaluate the first generation. For the total time, the difference between Methods A and B in \( t \) is 6.03, and \( P = 0.00 < 0.05 \). It can be seen that Method B has a significant impact on the total time compared to Method A, and the average time is reduced by 27.14 s. In the same way, Method C has a significant impact on the total time compared to Methods A and B, with 16.04 s and 43.18 s shorter, respectively.

Table 4. Paired-sample T test of the time used to evaluate the first-generation and total time used with Methods A, B and C.

| Difference                  | Mean   | Std. Deviation | Std. Error | Mean   | t      | Sig. (2-Tailed) |
|-----------------------------|--------|----------------|------------|--------|--------|-----------------|
| Time used to evaluate       |        |                |            |        |        |                 |
| first-generation Method A vs. B | -1.83  | 3.25           | 1.15       | -1.59  | 0.16   |                 |
| Method B vs. C              | 2.14   | 5.52           | 1.95       | 1.10   | 0.31   |                 |
| Method A vs. C              | 0.31   | 5.26           | 1.86       | 0.17   | 0.87   |                 |
| Method A vs. B              | 27.14  | 12.72          | 4.50       | 6.03   | 0.00   |                 |
| Method B vs. C              | 16.04  | 9.56           | 3.38       | 4.75   | 0.00   |                 |
| Method A vs. C              | 43.18  | 10.13          | 3.58       | 12.06  | 0.00   |                 |
| Total time used             |        |                |            |        |        |                 |
| Method A vs. B              |        |                |            |        |        |                 |
| Method B vs. C              |        |                |            |        |        |                 |
| Method A vs. C              |        |                |            |        |        |                 |

These results show that the clustering strategy is beneficial to reduce the total time, but it has no significant effect on the initial evaluation time. This shows that the clustering strategy can improve the individual evaluation, but it has no obvious impact on the cognition process of design tasks in the early stage of evolution. This also reflects the findings in the literature [19]. In addition, the “explicit–implicit” fused clustering method or Method C offers significant advantages in reducing the total time, and is superior to the traditional and clustering methods based on only the Hausdorff distance, thus revealing that the clustering results are consistent with the cognitive characteristics of users after comprehensively considering the explicit styling features and the implicit perceptual images. These results reflect the views that image classification based on color (explicit) and content (implicit) is more in line with user emotions [38].

As for Methods D and E, a paired sample T test was performed, and the analysis results are shown in Table 5. For the time required to produce the first-generation, the difference between Methods D and E in \( t \) is 5.02, and \( p = 0.002 < 0.05 \), thus indicating that Method E has a significant impact on the time required to evaluate the first-generation as opposed to Method D, with an average reduction of 7.78 s. In the same way, it can be seen that Method E has a significant impact on the total time used compared to Method D, and the total time is reduced by 21.75 s.

Table 5. Paired-sample T test of the time used to produce the first-generation and total time used with Methods D and E.

| Difference                  | Mean   | Std. Deviation | Std. Error | Mean   | t      | Sig. (2-Tailed) |
|-----------------------------|--------|----------------|------------|--------|--------|-----------------|
| Time used to evaluate       |        |                |            |        |        |                 |
| first-generation Method D vs. E | 7.78   | 4.38           | 1.55       | 5.02   | 0.00   |                 |
| Total time used             |        |                |            |        |        |                 |
| Method D vs. E              | 21.75  | 5.87           | 2.08       | 10.48  | 0.00   |                 |

Compared with the method in Zeng et al. [16], the proposed method has a significant reduction in both the time used to evaluate the first-generation and the total time, which means that the cognitive intervention method adopted in this paper is helpful for users to create the association between dissimilar information in the early stage of evolution and the association between similar information
in the evaluation process. Therefore, the proposed method improves the efficiency of creating cognitive association, reduces the consumption of cognitive resources for users, and is applicable in SUV styling design.

5. Conclusions

This paper examines the cognitive association of users during the IED process for product styling, and deconstructs the cognitive process into the association of dissimilar and similar information based on the cognitive characteristics for the product styling process of designers. In addition, a mapping model and a clustering strategy are constructed for the association of dissimilar and similar information, respectively. The proposed method is applied to the IED of the profile of an SUV. Experimental results show that the proposed method effectively reduces the initial time and total time for users to conduct the interactive evolutionary design, which helps to improve the efficiency of product styling design based on interactive evolutionary computing. The deconstruction of IED of product styling from the perspective of cognitive association is a new idea and direction to improve the efficiency of evolutionary design. In addition, the case study of SUV styling based on IED is a reference for adopting intelligent algorithms to design specific product styling in the design industry.

However, the method proposed in this paper has the following limitations: First, the mapping model of association between dissimilar information from design tasks to styling features, comprehensively considers the perceptual evaluation of multiple users, and is established to reflect universality. The mapping model reflects the common cognitive characteristics of users, but it is difficult to reflect the cognitive differences of different users. Therefore, in the next step, we will attempt to use a data mining method to establish a mapping model that meets the cognitive characteristics of different users. Second, a multiple linear regression is used in this paper to build the mapping model. Although the computational cost is low, due to the fact that the relationship between the perceptual images and styling features is not a simple linear relationship, its accuracy is worthy of further study. In future research, we will attempt to apply machine learning methods (such as neural networks) to study the performance of different methods for building mapping models. In addition, the proposed method is currently aimed at product styling design. In the future, we plan to conduct research on the product functional design, and explore methods to establish association between functional requirements and function attributes of the existing product.

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References

1. Wang, T.; Zhou, M. New Production Development and Research Based on Interactive Evolution Design and Emotional Need. In Proceedings of the International Conference on Human-Computer Interaction (HCII 2020), Copenhagen, Denmark, 19–24 July 2020; Springer: Cham, Switzerland, 2020; pp. 221–237.
2. Wang, T.; Zhou, M. A method for product form design of integrating interactive genetic algorithm with the interval hesitation time and user satisfaction. Int. J. Ind. Ergon. 2020, 76, 102901. [CrossRef]
3. Guo, Y.-N.; Zhang, X.; Gong, D.-W.; Zhang, Z.; Yang, J.-J. Novel Interactive Preference-Based Multiobjective Evolutionary Optimization for Bolt Supporting Networks. IEEE Trans. Evol. Comput. 2019, 24, 750–764. [CrossRef]
4. Cheng, S.; Dey, A.K. I see, you design: User interface intelligent design system with eye tracking and interactive genetic algorithm. CCF Trans. Pervasive Comput. Interact. 2019, 1, 224–236. [CrossRef]
5. Yang, Y.; Tian, X. Combing Users’ Cognition Noise with Interactive Genetic Algorithms and Trapezoidal Fuzzy Numbers for Product Color Design. *Comput. Intel. Neurosci.* 2019, 2019, 1019749.

6. Lv, J.; Zhu, M.; Pan, W.; Liu, X. Interactive Genetic Algorithm Oriented toward the Novel Design of Traditional Patterns. *Information* 2019, 10, 36. [CrossRef]

7. Leealathakul, N.; Rimbcharoen, S. Generating Kranok patterns with an interactive evolutionary algorithm. *Appl. Soft. Comput.* 2020, 89, 106121. [CrossRef]

8. Takenouchi, H.; Tokumaru, M. Interactive Evolutionary Computation System Using Multiple Users’ Gaze Information Considering User’s Partial Evaluation Participation. In Proceedings of the 2019 IEEE 10th International Conference on Awareness Science and Technology (ICAST 2019), Morioka, Japan, 23–25 October 2019.

9. Cascini, G.; O’hare, J.; Dekoninck, E.; Becattini, N.; Boujut, J.-F.; Ben Guefrache, F.; Carli, I.; Caruso, G.; Giunta, L.; Morosi, F. Exploring the use of AR technology for co-creative product and packaging design. *Comput. Ind.* 2020, 123, 103308. [CrossRef]

10. Zha, X.; Huang, C.; Yan, Y.; Guo, J. Progress of Foreign Cognitive Load Theory Application Research. *J. China Soc. Sci. Technol. Inf.* 2020, 39, 547–556. (In Chinese) [CrossRef]

11. Simon, H.A. Information processing models of cognition. *Annu. Rev. Psychol* 1979, 30, 363–396. [CrossRef]

12. Wang, H. Research on Information Design and Evaluation Method of Digital Interface Based on Cognitive Mechanism; Southeast University: Nanjing, China, 2015;

13. Zeng, D.; Gong, D.; Li, M.; Li, N. Thinking Fixation Strategy in Product Form Design and Its Application. *J. Mech. Eng.* 2017, 53, 58–65. (In Chinese) [CrossRef]

14. Khan, S.; Gunpinar, E.; Sener, B. GenYacht: An interactive generative design system for computer-aided yacht hull design. *Ocean Eng.* 2019, 191, 106462. [CrossRef]

15. Mok, P.Y.; Xu, J.; Wang, X.X.; Fan, J.T.; Kwok, Y.L.; Xin, J.H. An IGA-based design support system for realistic and practical fashion designs. *Comput. Aided Des.* 2013, 45, 1442–1458. [CrossRef]

16. Poirson, E.; Petiot, J.-F.; Blumenthal, D. Interactive Genetic Algorithm to Collect User Perceptions. Application to the Design of Stemmed Glasses. In *Nature-Inspired Methods for Metaheuristics Optimization*; Bennis, F., Bhattachariya, R., Eds.; Springer: Cham, Switzerland, 2020; pp. 35–51.

17. Mizutani, K.; Nakanowatari, D. Design of Japanese Characters using an Interactive Genetic Algorithm. In Proceedings of the 2019 IEEE 1st Global Conference on Life Sciences and Technologies (LifeTech 2019), Osaka, Japan, 12–14 March 2019.

18. Tomczyk, M.K.; Kadzinski, M. Decomposition-Based Interactive Evolutionary Algorithm for Multiple Objective Optimization. *IEEE Trans. Evol. Comput.* 2020, 24, 320–334. [CrossRef]

19. Zeng, D.; Zhou, Z.; He, M.; Tang, C. Solution to Resolve Cognitive Ambiguity in Interactive Customization of Product Shape. *Int. J. Comput. Intell. Syst.* 2020, 13, 565–575. [CrossRef]

20. de Koning, B.B.; Rop, G.; Paas, F. Effects of spatial distance on the effectiveness of mental and physical integration strategies in learning from split-attention examples. *Comput. Hum. Behav.* 2020, 110, 106379. [CrossRef]

21. Sweller, J.; Ayres, P.; Kalyuga, S. *Cognitive Load Theory*; Springer: New York, NY, USA, 2011. [CrossRef]

22. Veejaert, L.; Du Bois, E.; Moons, I.; Karana, E. Experiential characterization of materials in product design: A literature review. *Mater. Des.* 2020, 190, 108543. [CrossRef]

23. Petiot, J.-F.; Yannou, B. Measuring consumer perceptions for a better comprehension, specification and assessment of product semantics. *Int. J. Ind. Ergon.* 2004, 33, 507–525. [CrossRef]

24. Zuo, Y.X.; Wang, Z.Y. Subjective Product Evaluation System Based on Kansei Engineering and Analytic Hierarchy Process. *Symmetry* 2020, 12, 1340. [CrossRef]

25. Do Bagus, M.R.; Tomohiro, M. Conjoint Analysis of Costumers’ Preferences with Kansei Engineering System for Product Exterior Design. In Proceedings of the 2016 5th IIAI International Congress on Advanced Applied Informatics (IIAI-AAI 2016), Kumamoto, Japan, 10–14 July 2016; pp. 1026–1032.

26. Huttenlocher, D.P.; Klanderman, G.A.; Rucklidge, W.J. Comparing Images Using the Hausdorff Distance. *IEEE Trans. Pattern Anal. Mach. Intell.* 1993, 15, 850–863. [CrossRef]

27. Kumar, K.S.; Manigandan, T.; Chitra, D.; Murali, L. Object recognition using Hausdorff distance for multimedia applications. *Multimed. Tools Appl.* 2020, 79, 4099–4114. [CrossRef]

28. Tinh, B.T.; Nhan, T.T.; Chau, D.N. A method to reduce the computational cost of Modified Hausdorff Distance in Face Recognition. In Proceedings of the 2019 6th National Foundation for Science and Technology Development (NAFOSTED) Conference on Information and Computer Science (NICS), Hanoi, Vietnam, 12–13 December 2019; pp. 103–108.
29. Ozbay, S.; Safar, M. Real-Time Sign Languages Recognition based on Hausdorff distance, Hu invariants and Neural Network. In Proceedings of the 2017 International Conference on Engineering and Technology (ICET), Antalya, Turkey, 21–23 August 2017.

30. Fiorineschi, L.; Rotini, F. Unveiling the Multiple and Complex Faces of Fidelity. In Proceedings of the Design Society: International Conference on Engineering Design; Cambridge University Press: Cambridge, UK, 2019; pp. 1723–1732.

31. Michalek, J.J.; Ebbes, P.; Adiguzel, F.; Feinberg, F.M.; Papalambros, P.Y. Enhancing marketing with engineering: Optimal heterogeneous markets. *Int. J. Res. Mark.* 2011, 28, 1–12. [CrossRef]

32. Su, J.; Zhang, Q.; Wu, J.; Liu, Y. Evolutionary design of product multi-image styling. *Comput. Integr. Manuf. Syst.* 2014, 20, 2675–2682. (In Chinese)

33. Luo, S.; Li, W.; Fu, Y. Consumer Preference-driven SUV Product Family Profile Gene Design. *J. Mech. Eng.* 2016, 52, 173–181. (In Chinese) [CrossRef]

34. Wang, Z.; Liu, W.; Yang, M.; Han, D. Product form image design based on elliptic Fourier. *Comput. Integr. Manuf. Syst.* 2020, 26, 481–495. (In Chinese)

35. Green, A.E.; Cohen, M.S.; Kim, J.U.; Gray, J.R. An explicit cue improves creative analogical reasoning. *Intelligence* 2012, 40, 598–603. [CrossRef]

36. Darani, Z.S.; Kaedi, M. Improving the interactive genetic algorithm for customer-centric product design by automatically scoring the unfavorable designs. *Hum.-Cent. Comput. Inf. Sci.* 2017, 7, 38. [CrossRef]

37. Dou, R.; Zong, C.; Li, M. An interactive genetic algorithm with the interval arithmetic based on hesitation and its application to achieve customer collaborative product configuration design. *Appl. Soft Comput.* 2016, 38, 384–394. [CrossRef]

38. Song, J.; Han, K.; Lee, D.; Kim, S.W. Understanding Emotions in SNS Images From Posters’ Perspectives. In Proceedings of the 35th Annual ACM Symposium on Applied Computing (SAC), Prague, Czech, 30 March–3 April 2020.

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