SHAPE GENERATION SYSTEM FOR OPTIMIZING AESTHETIC INTEREST ASSOCIATED WITH NOVELTY AND COMPLEXITY

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ABSTRACT

Design aesthetics are one of the most important factors affecting the attractiveness of industrial products. Psychological theory suggests that a moderate level of novelty and complexity yields pleasant feelings in users. A design that is initially surprising to consumers and acceptable over time requires aesthetic interest associated with its novelty and complexity. In this study, we formulated the perceived novelty and complexity of a closed contour shape. Based on this formulation, we developed "Hybrid-GAN," which is a shape-generation system capable of generating a variety of shapes of arbitrary novelty and complexity. In a series of experiment, we obtained subjective evaluations of novelty and complexity, as well as beauty and interest, for the generated shape samples. The results indicated that our novelty and complexity formulations had significant positive correlations with subjective evaluations. The sum of the formulated novelty and complexity also had a significant positive correlation with interest. The results of this study are expected to be used to support the design of attractive shapes by providing feedback to designers regarding the degrees of novelty and complexity that users find most pleasant.

Keywords: Design for X (DfX), Design engineering, Complexity, Computational design methods

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1 INTRODUCTION

1.1 Importance of aesthetic interest in product design

Styling aesthetics are an important factor for making products more attractive and competitive in the marketplace, even when the appearance of a product may seem irrelevant to its performance (Yamamoto and Lambert, 1994). In his most advanced and acceptable (MAYA) principle, industrial designer R. Loewy (1951) stated that a successful design must be as innovative (or novel) as possible, but not so much as to be considered unacceptable. Murakami et al. (2011) formalized the positive and negative emotions that arise from the gap between the expectations and reality of a product and proposed a framework to support product design that considers these emotions. Yanagisawa et al. (2016; 2019; 2023) mathematically formulated the discrepancy between prediction and recognition, and the emotions associated with novelty using Bayesian inference. Their mathematical model suggests that the extent of surprise regarding a novel stimulus determines either positive or negative emotions.

In a study modelling visual aesthetic preferences, Graf and Landwehr (2015) hypothesized that people assess aesthetic preference through dual processes that they referred to as the "automatic process" and "controlled process." This model is called the pleasure-interest model of aesthetic kings (PIA model). The automatic process refers to beauty that is judged unconsciously and rapidly. The controlled process refers to beauty that is judged consciously and slowly after the automatic process. Aesthetic feelings under automatic processing are called pleasure, whereas aesthetic feelings under controlled processing are called interest. The factors that cause these aesthetic feelings are explained by the fluency of information processing. In automatic processing, people evaluate visual stimuli with high fluency (i.e., easy to process) as beautiful. In contrast, in controlled processing, people evaluate a visual stimulus that is disfluent under the automatic condition as unpleasant and evaluate a stimulus as interesting when disfluency decreases through further information processing (i.e., disfluency reduction). People rate a stimulus that is merely fluent as boring under controlled processing. Yanagisawa et al. formulated such emotions by associating the fluency-disfluency paradigm with free energy dynamics and revealed comprehensive conditions of interest (Yanagisawa et al., 2022).

To achieve an attractive styling design that will surprise consumers and be accepted over time, as described by the MAYA principle, we place greater importance on aesthetic interest than on pleasure. This is because surprise and novelty introduce a certain amount of disfluency and its subsequent reduction, which induce interest.

The psychologist Berlyne (1970) proposed the arousal potential theory and stated that a moderate level of novelty and complexity yield pleasant feelings. Yanagisawa (2021) mathematically formulated arousal potential based on the sum of the information content caused by novelty and complexity. Figure 1 presents the relationship between arousal potential and hedonic value (pleasantness or unpleasantness of an emotion), which is referred to as a Wundt curve.

Based on the background presented above, we hypothesize that the arousal induced by the novelty and complexity of an aesthetic shape plays the role of disfluency reduction in the PIA model and lets people perceive interest. Therefore, we focus on the novelty and complexity of shapes as sources of aesthetic interest.

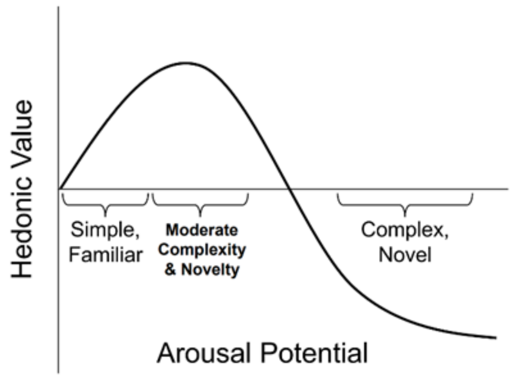

Figure 1. Wundt curve. A moderate level of arousal potential induces a positive hedonic response, but an extreme arousal potential induces negative responses.

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1.2 Shape generation system for styling design

Product designers who perform styling design use their extensive experience and various principles to diverge their concepts into various design ideas (Runco and Acar, 2012) before converging to a final design (Ghiselin, 1960). Although these iterations of divergent and convergent thinking are prominent in design research (Goldschmidt, 2016), they are typically laborious manual tasks that require significant time.

To support this process, several studies (Yanagisawa and Fukuda, 2005; Li et al., 2021; Yang, 2011; Mata et al., 2019; Wang et al., 2022; Tang et al., 2013; Kelly et al., 2011; Giannini et al., 2006; Yanagisawa, 2011) have been conducted on shape generation systems considering user emotions in the field of Kansei engineering and affective design.

These studies have considered with various emotions toward products such as cups (Yanagisawa and Fukuda, 2005), vases (Mata et al., 2019), and automobiles (Wang et al., 2022). In these studies, models for evaluating emotions relied on subjective evaluations. However, subjectivity reflects individual differences such as the preferences and personalities of those who evaluate shapes, meaning such evaluations lack generality. Additionally, the application of such systems is limited to specific products.

In the previous section, we defined the aesthetic interests associated with novelty and complexity as aesthetic elements of a product. If novelty and complexity can be described as features, we believe it should be possible to develop a shape-generation system without subjective evaluations.

In this study, we developed a shape generation system that allows users to manipulate the perceived novelty and complexity of a contour shape to maximize its perceived interest. We experimentally demonstrate that the proposed system generates aesthetically interesting shapes. We have also detailed the proposed system in our previous work (Honda et al., 2022). Our three objectives are as follows:

1. To formulate and validate indices for the novelty and complexity of closed-contour shapes.
2. To develop a shape generation system that independently manipulates novelty and complexity.
3. To verify whether the shapes generated by the system are aesthetically interesting for controlled processing, by comparing the evaluation with automatic processing.

Our previous work (Honda et al., 2022) lacks a discussion of whether the subjective ratings of aesthetic interest were made with automatic or controlled processing, as claimed in the PIA model (Graf and Landwehr, 2015). The distinction between the two types of processing is important, since the trend of the aesthetic evaluation varies depending types of processing. Therefore, in this study, we conducted the additional experiments in section 3.2. to distinguish which process the evaluation was performed in. This additional experiment corresponds to the objective 3 and is an update of this study compared to the previous work.

The remainder of this paper is organized as follows. Section 2 describes the methodology adopted in this study. Section 3 presents and discusses experiments conducted to evaluate the proposed system. Finally, Section 4 summarizes our main conclusions.

2 METHODS

2.1 Formulation of the novelty and complexity of contour shapes

2.1.1 Quadratic curvature entropy (QCE) as complexity

We formulated complexity using QCE (Ujiie et al., 2012). QCE is the information entropy of the transition probabilities calculated from a contour shape by defining a curvature function whose argument is the length of the curve. QCE is defined such that the more diverse the transitions in curvature values, the greater the value.

QCE has been experimentally demonstrated to correlate with the macroscopic complexity of shapes (Ujiie et al., 2012). It has also been applied in product design research as an indicator of the macroscopic information content of a shape (Lu et al., 2021).

2.1.2 Fourier principal component distance (FPCD) as novelty

We formulated novelty using an original metric called the FPCD. The FPCD expresses the degree to which a shape deviates from a typical shape (in the case of an automobile, it would be a typical automobile shape or prototype) as the distance between the two shapes in terms of the global features

of the shape. We adopted the principal component scores of the elliptic Fourier descriptor (EFD) (Kuhl and Giardina, 1982) to represent global features.
The EFD was used in conjunction with principal component analysis to classify contour shapes accurately based on their macroscopic forms. This descriptor has been applied to the classification of objects such as cereal grains and appliances (Mebatsion et al., 2012; Choudhury and Tjahjadi, 2012; Baets et al, 2018).

2.2 Hybrid-GAN: proposed shape generation system

2.2.1 System overview

Based on the novelty and complexity formulations described in Section 2.1, we developed a system called Hybrid-GAN (HGAN) (Figure 2) that independently controls these values to generate shapes. The proposed system consists of a three-element loop containing a generator (<2>), feature calculation module (<3>), and optimization module (<5> and <6>). The generator generates a shape and calculates novelty and complexity indices (FPCD and QCE). The shape is then optimized to minimize the distances to the target FPCD and QCE values. By repeating this loop, the system generates shapes with the desired FPCD and QCE values without relying on subjective user evaluations.
The generator of the proposed system is a type of deep generative model called a generative adversarial network (GAN) using a method called progressive growth of GANs (Karras et al., 2018). It can be used to generate high-resolution images. We adopted particle swarm optimization (PSO) (Kennedy and Eberhart, 1995), which is a widely used metaheuristic for continuous variables.

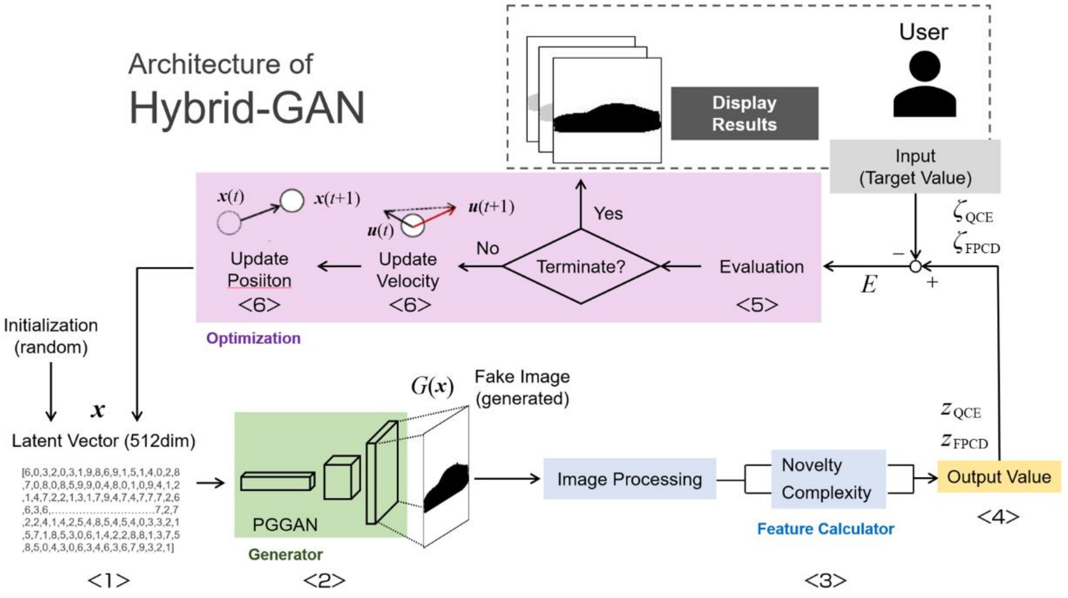

Figure 2. Overview of the HGAN shape generation system.

2.2.2 Algorithm

The flow of HGAN calculations is presented in Figure 2. Numbers <1> to <6> in the figure correspond to the following procedures:

1. P initial position vectors $\boldsymbol{x}$ with 512 dimensions are randomly generated as an initial population according to a normal distribution.
2. The generator deconvolutes each of the P vectors into P shape silhouette images $G(\boldsymbol{x})$ with a resolution of 512 × 512 pixels. Then, the program performs a series of image processing steps, binarizes the image, detects contours, and thins out the contour points equally into S pieces.
3. Novelty and complexity indices (i.e., QCE and FPCD) are calculated for each shape.
4. Each calculated index is converted into a Z-score.
5. The following loss function E is calculated for each of the P shape images:

$$E = |z_{\mathrm{QCE}} - \varsigma_{\mathrm{QCE}}| + |z_{\mathrm{FPCD}} - \varsigma_{\mathrm{FPCD}}|, \tag{1}$$

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where z_{QCE} and z_{FPCD} denote the Z-scores of the individual QCE or FPCD values, respectively, and ς denotes the Z-score of the fixed target value set by the user.

6. PSO is performed on the position vector $\boldsymbol{x}$ to minimize E. We let $\widehat{\boldsymbol{x}_g}$ be the position with the smallest E value among all vectors yet to be obtained and let $\widehat{\boldsymbol{x}}$ be the position with the smallest E value among the obtained positions. The system then updates the position $\boldsymbol{x}$ and velocity $\boldsymbol{u}$ of each particle according to the following equations:

$$\boldsymbol{x} \leftarrow \boldsymbol{x} + \boldsymbol{u}, \tag{2}$$

$$\boldsymbol{u} \leftarrow w\boldsymbol{u} + c_1 r_1 (\widehat{\boldsymbol{x}} - \boldsymbol{x}) + c_2 r_2 \left(\widehat{\boldsymbol{x}_g} - \boldsymbol{x}\right), \tag{3}$$

where w is the weight of the inertia term, $c_1 r_1$ is the weight of the term attempting to reach the best position for each particle, and $c_2 r_2$ is the weight of the term attempting to reach the best position among all particles. Here, c_1 and c_2 are constants, and r_1 and r_2 are random numbers between zero and one.

7. The updated positions $\boldsymbol{x}$ are used to generate new images in step 2. After performing steps 2 to 6 over n_g generations, the system obtains a solution that is closer to the target value. If the value of the loss function E is less than the constant E_{max}, then shape optimization is considered to be successful.

3 EXPERIMENTS

3.1 Experiment 1: evaluation of aesthetic interest using generated shapes

3.1.1 Objectives and hypotheses

The objective of this experiment was to test the validity of the novelty and complexity indices formulated in Section 2.1 and to investigate the impact of the novelty and complexity indices on perceived aesthetic interest. We conducted Experiment 1 to obtain subjective evaluations of novelty and complexity, as well as subjective evaluations of the beauty and interest of samples based on automobile shapes generated by the HGAN system. Our three hypotheses regarding this experiment are defined as follows:

- QCE is positively correlated with subjective ratings of complexity. (H1)
- FPCD is positively correlated with subjective ratings of novelty. (H2)
- The subjective rating of interest has an inverse U-shaped relationship with the sum of QCE and FPCD. In other words, when the relationship between the two is approximated by a quadratic function, the curve is convex upward. (H3)

Figure 3 presents the relationships between variables in our experimental hypotheses. In particular, H3 assumes that the sum of QCE and FPCD corresponds to arousal potential and that aesthetic interest is inversely U-shaped with respect to arousal potential.

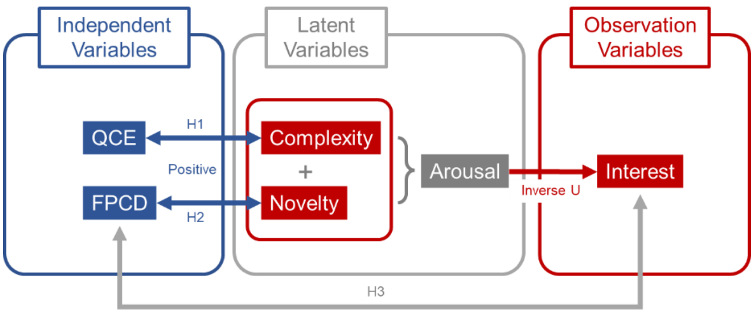

Figure 3. Relationships among variables in our experimental hypotheses.

3.1.2 Stimuli

The presented stimuli were side-view images of profiles of automobiles, as shown in Figure 4. We considered automobile exterior styles because they have a variety of shapes and their differences in shape are relevant to their aesthetic evaluations. Profiles were generated by dividing the FPCD and QCE values into six bins. An "×" symbol indicates that the system could not generate any images

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whose loss function E value in Eq. (1) was less than $E_{max} = 1$ in two attempts. We printed each stimulus on a 68 mm square card and presented the stimuli to evaluators.

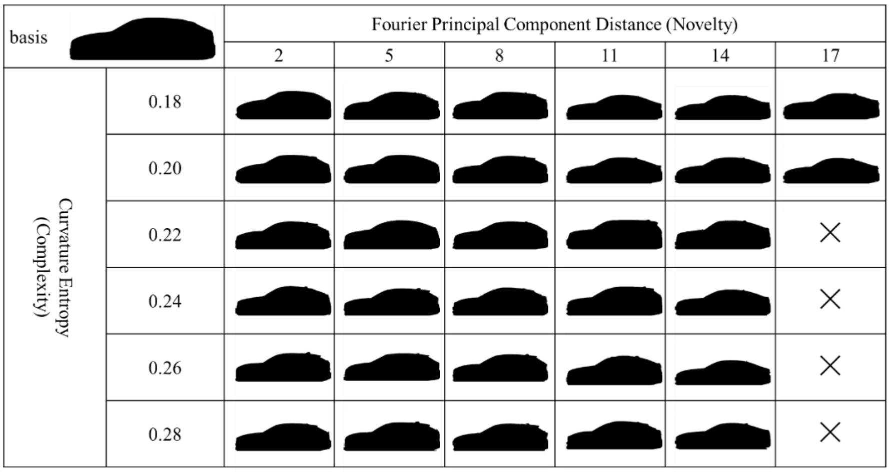

Figure 4. Experimental stimuli (automobile shapes, 32 images). We used the basis (top left) image as the reference geometry for calculating FPCD.

3.1.3 Participants

We recruited 24 participants (13 males and 11 females) who met the following criteria: university students in their 20s, healthy with no visual illness or disability, no psychological resistance to automobiles, and comfortable with experiments conducted in the dark.

In accordance with the principles of the Declaration of Helsinki, all participants provided written informed consent before their participation in this study. Participants were allowed to interrupt the experimental sessions at any time.

3.1.4 Procedure

Participants rated the samples subjectively by sorting the stimuli on a nine-point scale for novelty and complexity, and beauty and interest. The experimenter instructed participants to "evaluate the shape consciously once you have observed it." This instruction was intended to encourage evaluation during controlled processing, which leads to aesthetic interest. The study protocol was approved by the Ethics Committee of the Graduate School of Engineering at the University of Tokyo (no. KE21-94).

3.1.5 Analysis

We used Likert scales based on the semantic differential method (Osgood, Suci, & Tannenbaum, 1957) to measure the novelty, complexity, interest, and beauty of shapes. According to Table 1, we considered each of the ratings on a nine-point scale and obtained mean values for each sample.

Table 1. Evaluation terms and ratings

<table>
<tr><th>Item</th><th>Term</th><th colspan="9">Rating</th><th>Term</th></tr>
<tr><td>Complexity</td><td>Simple</td><td rowspan="4">1</td><td rowspan="4">2</td><td rowspan="4">3</td><td rowspan="4">4</td><td rowspan="4">5</td><td rowspan="4">6</td><td rowspan="4">7</td><td rowspan="4">8</td><td rowspan="4">9</td><td>Complex</td></tr>
<tr><td>Novelty</td><td>Typical</td><td>Novel</td></tr>
<tr><td>Beauty</td><td>Ugly</td><td>Beautiful</td></tr>
<tr><td>Interest</td><td>Boring</td><td>Interesting</td></tr>
</table>

3.1.6 Results

The results of our analysis using the statistical software R confirmed significant positive correlations between complexity and QCE ($R2 = 0.34$, $F = 15.7$, $t = 0.81$, $p < 0.01$), and between novelty and FPCD ($R2 = 0.33$, $F = 14.8$, $t = 3.85$, $p < 0.01$). These results support H1 and H2, indicating the validity of our formulations.

A quadratic fitting between the sum of QCE and FPCD, and subject rating of interest revealed that the coefficient of x^2 was not significantly negative ($t = -0.59$, $p > 0.1$), which does not support H3.

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However, the results confirmed a significant positive correlation between the two variables ($R2$ = 0.32, F = 13.8, t = 3.72, p < 0.01), as illustrated in Figure 5. Here, we set the ratio of the weights of QCE and FPCD to 0.33:0.67 to maximize R2.

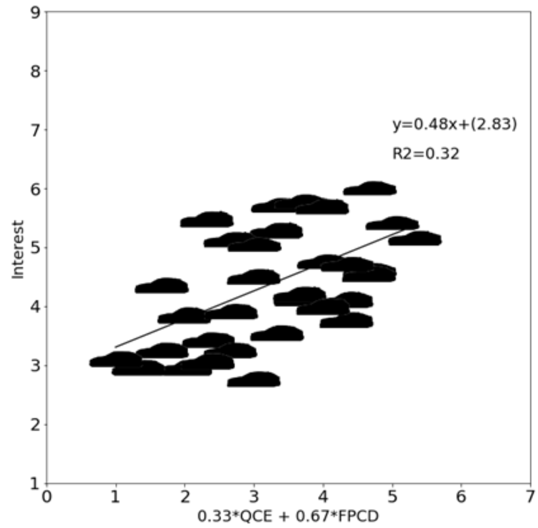

Figure 5. Scatter diagram of the sum of QCE and FPCD versus subject ratings of interest for automobile shapes.

3.1.7 Discussion

Regarding H3, the experimental results in Figure 5 reveal a monotonically increasing relationship between the sum of QCE and FPCD, and the subject ratings of interest, rather than an inverted U-shaped relationship. This could be attributed to the small novelty and complexity of the samples. This may have led to the emergence of a region of low arousal potential in the Wundt curve ("Simple, Familiar," a monotonically increasing region in Figure 1).

However, the significant positive correlation between the sum of QCE and FPCD, and the subject ratings of interest suggests the (1) validity of focusing on novelty and complexity as functions of aesthetic interest and that (2) adjusting FPCD and QCE when generating shapes enhances aesthetic interest.

3.2 Experiment 2: distinguishing aesthetic evaluations between controlled and automatic processing by manipulating evaluation time

3.2.1 Objectives and hypotheses

In Experiment 1, we obtained subjective ratings of interest from participants by assuming that aesthetic evaluation was performed based on controlled processing in the PIA model. We confirmed higher subjective ratings of interest for "disfluent" shapes with higher novelty (FPCD) and complexity (QCE). If evaluations were performed based on automatic processing in Experiment 1, the results would be inconsistent with the feature of automatic processing, where "disfluent" visual stimuli cause feelings of displeasure.

However, based on the results and conditions of Experiment 1, it was not possible to determine whether the evaluations were performed using controlled or automatic processing. Therefore, we aimed to verify that the participants in Experiment 1 performed evaluations based on controlled processing, rather than automatic processing. In Experiment 2, we obtained the "aesthetic preferences" of samples in an experimental system designed such that participants were encouraged to perform evaluations based on automatic processing. Our hypotheses was defined as follows:

- The aesthetic preference ratings obtained in Experiment 2 should be reversed compared to the subjective ratings of "beauty" and "interest" obtained in Experiment 1. (H4)

In the PIA model described in Section 1.1., a fluent shape with low novelty and complexity is likely to be evaluated as "pleasurable" (positive) based on automatic processing, whereas it is likely to be evaluated as "boring" (negative) based on controlled processing. A disfluent shape with high novelty

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and complexity is likely to be evaluated as "unpleasant" (negative) based on automatic processing, whereas it is likely to be evaluated as "interesting" or "confusing" (positive or negative) based on controlled processing. Therefore, the positive and negative evaluations of the same shape can be reversed, leading to the confirmation of H4. Table 2 in Section 3.2.3 summarizes the arguments presented in this section.

3.2.2 Procedure

Participants responded to whether they liked or disliked the samples presented on the display through keyboard inputs ("F" for like and "J" for dislike). This process was repeated for the same 32 samples used in Experiment 1. The participants were the same as those in Experiment 1. The experimenter instructed the participants to respond as quickly as possible within 1 second. The aim of this time limit was to encourage participants to evaluate aesthetic preferences based on automatic processing, which is performed rapidly and unconsciously. Figure 6 presents a schematic of this experiment.

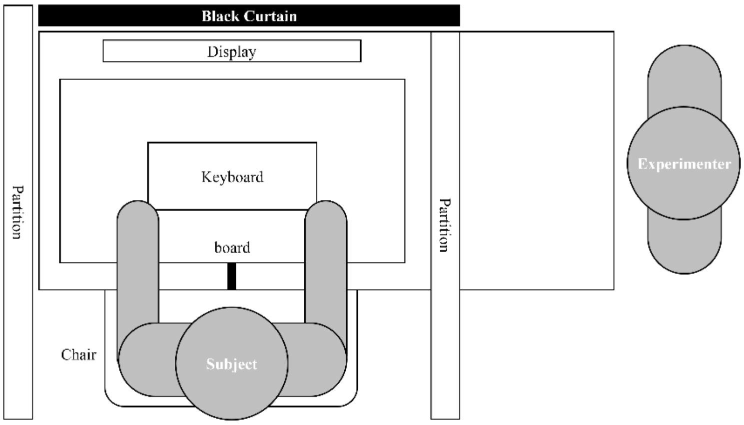

Figure 6. Schematic diagram of the experimental apparatus. There is a partition between the subject and experimenter so that they cannot see each other.

3.2.3 Analysis

In Experiment 2, we counted the number of participants who selected "like" for each sample. We then designated the samples whose numbers of likes were below the median as Group I and the others as Group II. In Experiment 1, we compared the ratings for "beauty" and "interest" between two groups.
Table 2 presents the correspondence between the ratings in the PIA model and experimental system as a basis for H4. Group I, which has low aesthetic preferences, contains samples that were rated as "unpleasant" based on the automatic process. Group II, which has high aesthetic preferences, contains samples that were evaluated as "pleasurable."

Table 2. Evaluation comparison between the PIA model and experimental system

		Experiment 1	Experiment 2
Processing		Controlled	Automatic
Evaluation	Group I	Interesting/Confusing (POS/NEG)	Unpleasant (NEG)
	Group II	Boring (NEG)	Pleasurable (POS)

3.2.4 Results

Figure 7 presents the subjective ratings of beauty and interest for Groups I and II, which are classified according to aesthetic preferences. A Wilcoxon rank-sum test conducted using the statistical software R revealed that the beauty of the samples in Group II was significantly lower than that of the samples in Group I (W = 199.5, p < 0.01). Interest in Group II was also significantly lower than that in Group I (W = 189.5, p < 0.05). These results support H4.

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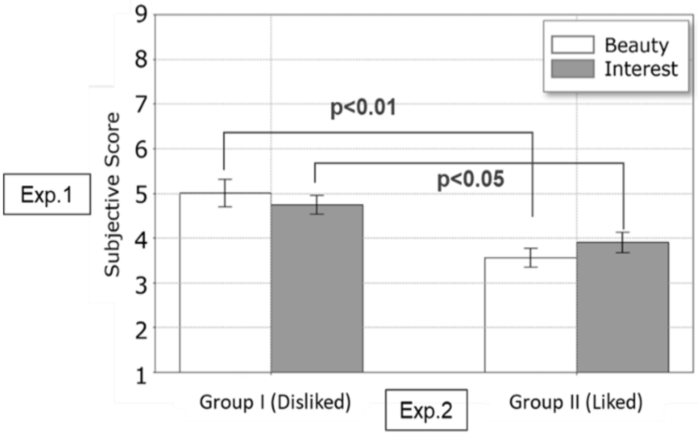

Figure 7. Subjective ratings of beauty and interest in each group classified according to aesthetic preferences

3.2.5 Discussion

In Experiments 1 and 2, the time spent evaluating the samples varied. As a result, the aesthetic evaluations of the same samples were reversed. The results suggest that controlled processing was dominant in Experiment 1. The results also reinforce the discussion in Section 3.1.6 regarding the effectiveness of the system observed in Experiment 1.

4 CONCLUSION

In this study, we developed a shape generation system (HGAN) that allows users to manipulate the perceived complexity and novelty of generated shapes to maximize their perceived aesthetic interest based on formulated novelty and complexity indices (i.e., FPCD and QCE, respectively). We experimentally investigated the effects of FPCD and QCE on perceived interest.

The experimental results suggest that manipulating FPCD and QCE can enhance the aesthetic interest of generated shapes. Additionally, by changing the time spent on subjective evaluation, we confirmed that the evaluation of aesthetic interest was performed based on the controlled process of dual-process perception (Graf and Landwehr, 2015).

We envision the user of the system as a product designer. The system presents shapes with varying degrees of control over novelty and complexity. By examining the customer's impressions of these shapes, the designer can obtain feedback on the degree of novelty and complexity that the customer finds most aesthetically interest.

The system has the limitation that it can only handle 2D closed curve contours. Future research on methods for calculating novelty and complexity from 3D shapes and shapes with internal color, as well as methods for generating such shapes, is desirable in order to increase the applicability of the system.

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