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NOVELTY INDEX FOR CURVED SURFACE USING KL DIVERGENCE AND ITS EFFECTIVENESS ON INDUSTRIAL PRODUCTS

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ABSTRACT

It is said that the relationship between "novelty" and hedonic response is expressed as an inverse U-shape. The latest studies about perception emphasize "novelty" as a factor of emotion and quantify "novelty" by assessing the difference in amount of information using Kullback-Leibler (KL) divergence. In this study, we proposed a novelty index of closed surfaces using KL divergence focusing on their curvatures. To calculate novelty index, we firstly calculated Gaussian curvature of each vertex in the shape. Then, we defined occurrence probability distribution which represents probability that a vertex has a certain curvature. The KL divergence expresses the difference between the occurrence probability distributions of the standard shape and the target shape. To confirm the effectiveness of the proposed index, we conducted the cognitive experiment using the shape samples of an automobile generated by particle swarm optimization method. The coefficient of determination between the proposed index and sensory evaluation values of "difference" were very high which support the applicability of the index. Furthermore, the consideration of location information increased the correlation with sensory evaluation. This suggests the possibility to evaluate an industrial design requirement quantitatively and contributes to develop the automatic shape generation in product design.

Keywords: *novelty, curvature, KL divergence, industrial products*

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1 INTRODUCTION

Recent development of computational technologies has enabled partially automation of the design process (Singh & Gu, 2012). Generative design is one of those computation-based design methods to realize multiple shape generation (Caetano, 2019, Lin & Lee,2013, Singh & Gu, 2012). However, conventional generative design methods evaluate the physical constraints (e.g., stress, stiffness and mass) (Shea, 2005, Sato, 2007), and few methods focus on the perceived "aesthetic liking". Hence, designers need to choose and refine a final design from the proposed design (Lin, 2013). If the method to evaluate the "aesthetic liking" of shapes could be developed, generative design can be performed without designers and causes a large impact on design industry.

In the industrial design field, many researchers have pointed out "novelty" influences the "aesthetic liking" of products. Hekkert (2003) conducted a cognitive experiment for industrial products and concluded "novelty" affect "aesthetic liking". Creusen (2015) insisted the "typicality" with a touch of "novelty" is preferred. Liu et al (2020) emphasized that "novelty" of utilitarian products increases and decreases preference when they are promotion-focused and prevention-focused, respectively. Berlyne (1970, 1971) insisted that moderate level of "novelty" is preferred.

This study aims to propose an index of "novelty" for industrial products, which is important for development of design evaluation in generative design. We, therefore, quantify "novelty" of closed surfaces and conduct a sensory evaluation experiment on "difference from the basic shape" using the automobile shapes, verifying the effectiveness of the proposed index.

2 PROPOSITION OF NOVELTY INDEX

2.1 Related works

The recent research on human perception provides effective guidelines for novelty index. Friston quantified the information content obtained by perceiving an object in the outside world by the Kullback-Leibler (KL) divergence (Friston, Kilner, & Harrison, 2006). Furthermore, Yanagisawa (2019, 2020) defined the "novelty" as the information content gained in the brain after perceiving sensory stimuli and proposed free-energy model of emotion potential. In this theory, "novelty" is formulated as the KL divergence of the posterior distribution from the prior distribution.

Previous researches indicate that curvature represents the overall shape feature quantitively and has the major influence on design evaluation (Ujiie, Kato, Sato & Matsuoka, 2012, Kato & Matsumoto, 2020). We, therefore, emphasize that curvature is effective to evaluate "novelty".

We decided to calculate the novelty index as the KL divergence of probability distributions defined by curvature of typical shape and that of input shape, respectively.

2.2 Proposition of novelty index

This study proposed Gaussian curvature KL divergence as an index of "novelty". This index calculates the difference between probability distributions of standard shape and target shape using KL divergence. Note that, we utilize the occurrence probability vector as a probability distribution. The calculation of Gaussian curvature KL divergence is described as follows.

1. The Gaussian curvature K is calculated at each sample point on the sampling surface, and the dimensionless Gaussian curvature K' is calculated by multiplying K by the square of the maximum diameter D of the curved surface shape.
2. Quantize K' by setting parameters (deviation E and number of states V) and assign K' of each sample points to each state s_i.
3. Occurrence probability of state s_i $(i \in \{1,2,\dots,V\})$ p_i is calculated as:

$$p_i = \frac{N_i}{N} \tag{1}$$

where, N_i and N are the numbers of vertices of state s_i and of all vertices on the surface, respectively. Then, the occurrence probability of the target and standard shapes can be expressed as the vector $\boldsymbol{p}^{\mathrm{target}} = p_i^{\mathrm{target}}$ and $\boldsymbol{p}^{\mathrm{standard}} = p_i^{\mathrm{standard}}$, respectively.

4. Gaussian curvature KL divergence $D_{\mathrm{KL}}\left(\boldsymbol{p}^{\mathrm{target}} \parallel \boldsymbol{p}^{\mathrm{standard}}\right)$ is calculated as:

$$D_{\mathrm{KL}}\left(\boldsymbol{p}^{\mathrm{target}} \parallel \boldsymbol{p}^{\mathrm{standard}}\right) = \sum_{i=1}^{V} p_i^{\mathrm{target}} \log_2 \frac{p_i^{\mathrm{target}}}{p_i^{\mathrm{standard}}} \tag{2}$$

5. In Eq. (2), we assume that p_i^{standard} is greater than zero if the corresponding p_i^{target} is greater than zero. If p_i^{standard} does not satisfy this property, we replace $\boldsymbol{p}^{\mathrm{standard}}$ in Eq. (2) with the following equation (McDonough et al., 2011).

$$\boldsymbol{p}^{\mathrm{standard}'} = (1-\varepsilon)\boldsymbol{p}^{\mathrm{standard}} + \left(\frac{\varepsilon}{V}\right)\boldsymbol{e} \tag{3}$$

where, ε is a parameter ranging from 0 to 1 ($\varepsilon = 0.0001$ is used in this study); $\boldsymbol{e}$ is a of ones.

3 COGNITIVE EXPERIMENT

3.1 Experimental conditions

This study conducted the experiment to confirm the correlation between the proposed index and human cognition. The conditions of the experiment are described as follows:

- Participants: 42 university students in their twenties (34 men and 8 women), including 24 general students and 18 students from automobile club with high interests on automobiles.
- Sample shapes: 37 sample shapes are generated by deforming standard shape (MAZDA MX-5, 3rd generation) using PSO shape generation method in order to realize wide range of “novelty” (Fig.1).
- Evaluation method: the sensory evaluation for “difference from the standard shape” based on the seven-point Likert scale (1: “strongly disagree”, 2: “disagree”, 3: “slightly disagree”,

4: "neither agree nor disagree", 5: "slightly agree", 6: "agree", 7: "strongly agree"), profiles of participants and evaluation criteria.

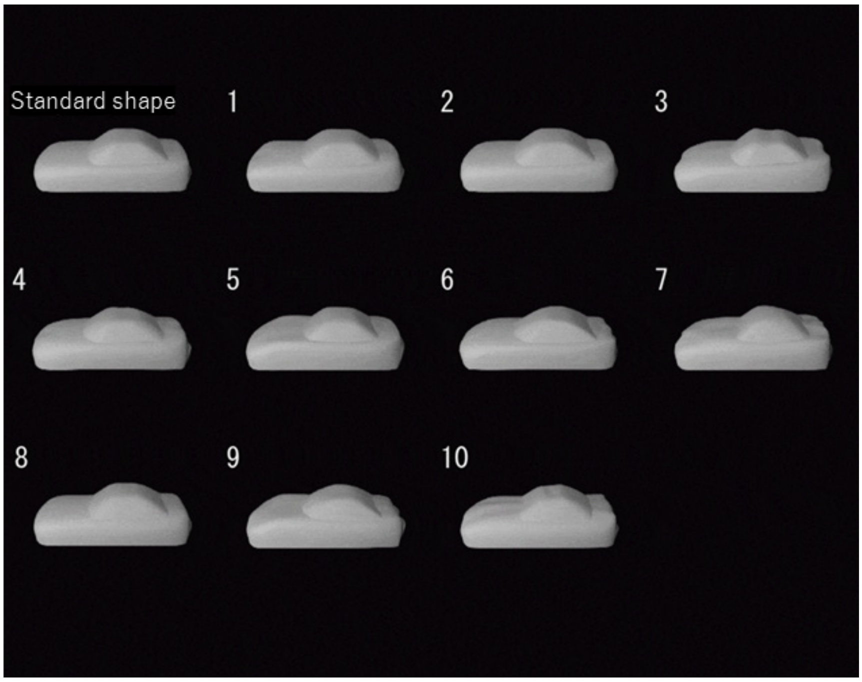

Figure 1. Examples of sample shapes

3.2 Results and discussions

The relationship between proposed novelty index and sensory evaluation values about "difference from the standard shape" is shown in Fig.2. The coefficient of determination R^2 in logarithmic approximation is 0.81 which confirms the correspondence between D_{KL} and the sensory evaluation values.

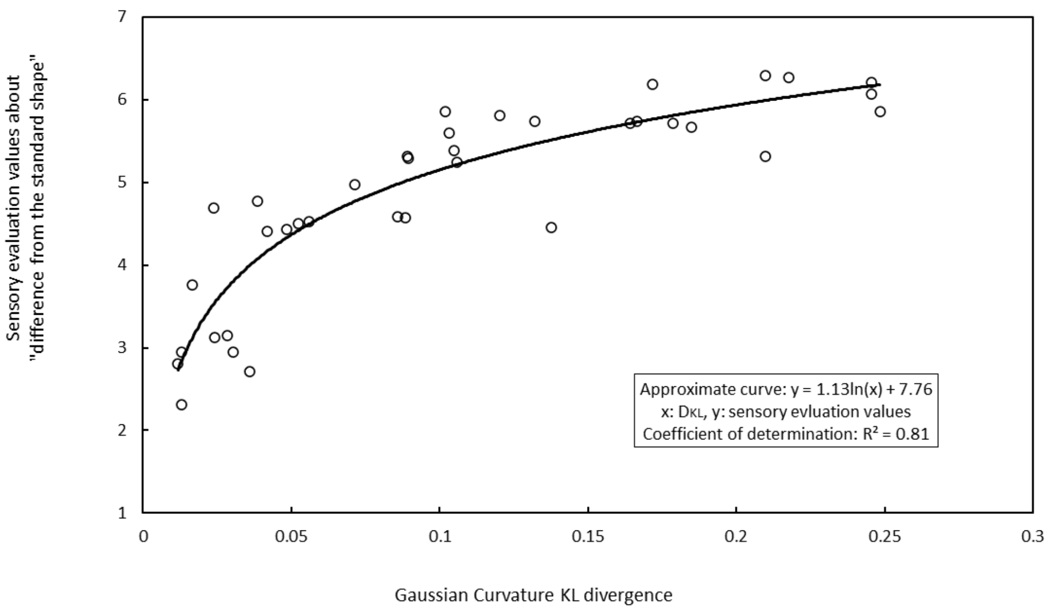

Figure 2. Relationship between Gaussian Curvature KL divergence and sensory evaluation values about "difference from the standard shape"

The result of questionnaire about the evaluation criteria shows that lots of participants focused on the roof and bonnet to evaluate the shapes. Moreover, several studies indicated that participants place importance on the evaluation from a familiar direction of the product in case of industrial products (e.g., the front side of the car) (Okano, 2020). Therefore, we considered to refine our novelty index to take into account of location information by adapting occurrence probability matrix described with quantized Gaussian curvature (V states) and quantized location information (M parts) to probability distributions of KL divergence. This index can also be weighted with correspondence to each part of shape, implying to be used as an index that reflects high influence on the difference of front part. The advanced Gaussian curvature KL divergence is defined as follows:

$$D_{\mathrm{KL}}\left(\mathbf{P}_{M\times V}^{\mathrm{target}} \parallel \mathbf{P}_{M\times V}^{\mathrm{standard}}\right) = \sum_{i=1}^{M}\sum_{j=1}^{V}\left(K_i \times p_{ij}^{\mathrm{target}} \log_2 \frac{p_{ij}^{\mathrm{target}}}{p_{ij}^{\mathrm{standard}}}\right) \tag{4}$$

where $\mathbf{P}_{M\times V}^{\mathrm{target}}$ and $\mathbf{P}_{M\times V}^{\mathrm{standard}}$ are $M \times V$ matrix of occurrence probability in target shape and standard shape, and K_i is the weighting coefficient, respectively. The relationship between this advanced index with weighting coefficient $K_i = 1$ at whole area and sensory evaluation values about "difference from the standard shape" is shown in Fig.3. The coefficient of determination R^2 in logarithmic approximation is 0.86. The same relation with weighting coefficient $K_i = 10$ at the front part of shape is shown in Fig.4. The coefficient of determination R^2 in logarithmic approximation is 0.87. These results signify that the consideration of location information and weighting by degree of attention enhance the correlation with sensory evaluation.

As an industrial contribution, this novelty index is effective as evaluation method of products and also has the applicability for the advanced generative design method which automatically generates aesthetic shapes evaluating the "novelty" of industrial products. Designers can choose the target value of this index, which corresponds to the preferred level of novelty.

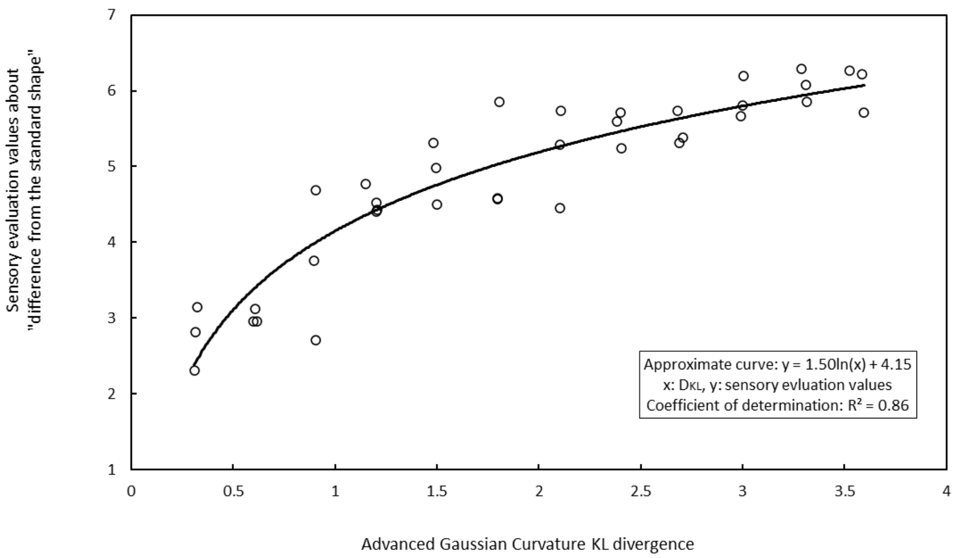

Figure 3. Relationship between Advanced Gaussian Curvature KL divergence (K=1) and sensory evaluation values about "difference from the standard shape"

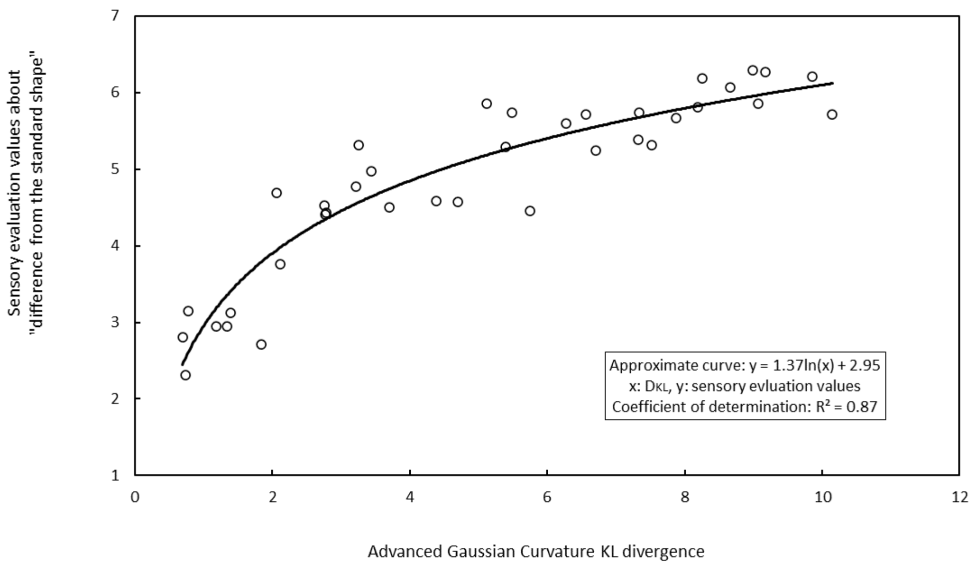

Figure 4. Relationship between Advanced Gaussian Curvature KL divergence (K=10) and sensory evaluation values about “difference from the standard shape”

4 CONCLUSION

This study proposed Gaussian curvature KL divergence as a novelty index of curved surface shape. Using this novelty index, we conducted a cognitive experiment using the shapes of automobiles which confirmed the effectiveness of proposed index with the coefficient of determination 0.81. Furthermore, consideration of location information provides better correlation with sensory evaluation. The future study should analyze the relationship between “novelty” and “aesthetic liking” and propose integral index of “aesthetic liking”.

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