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GENERATION OF PRODUCT DESIGN USING GAN BASED ON CUSTOMER'S KANSEI EVALUATION

Masakazu KOBAYASHI[1a], Pongsasit THONGPRAMOON[b]

[a] *Toyota Technological Institute, Japan, kobayashi@toyota-ti.ac.jp*

[b] *Toyota Technological Institute, Japan, pongsasit.thongpramoon@gmail.com*

ABSTRACT

In recent years, deep learning has attracted much attention and various techniques have been proposed. GAN (Generative adversarial networks) is one such method. GAN uses images as the training set and learns to generate new images that are indistinguishable from the training set. In this study, A GAN-based design method that generates new products from the images of the customer's favorite products is proposed. The product images that customers evaluated as preferable are used as the training set of GAN. If the GAN fulfills its capabilities properly, the images generated from a customer's favorite product are more likely to be preferred by the customer. In the case study, the proposed method was applied to chair design. The generated chair images were first evaluated in terms of image quality, and then evaluated by subjects.

Keywords: *Kansei engineering, aesthetic design, deep learning, GAN (Generative Adversarial Network)*

1 INTRODUCTION

Due to maturation of science and technology, it becomes increasingly difficult to differentiate products in terms of performance, functional feature or price. Therefore, companies are required to differentiate their products in terms of subjective and abstract qualities such as aesthetic and comfort that are evaluated by customer's feeling, which is called "Kansei" in Japanese. The quality evaluated by customer kansei is called "Kansei quality" (Yanagisawa 2011).

[1] Corresponding author.

In the field of Kansei engineering (referred to as affective or emotional engineering), various methods have been developed to capture customer kansei and utilize it in product design. Questionnaire-based methods like semantic differential (SD) method (Osgood & Suci 1967) are widely used to quantitatively measure customer's impressions of products. On the other hand, various types of methods such as artificial neural network (Hsiao & Huang 2002; Kobayashi, Kinumura &Higasi 2015), fuzzy set theory (Hsiao & Huang 1998), interactive reduct evolutionary computation (Yanagisawa & Fukuda 2004), multidimensional scaling (Kobayashi, Kinumura &Higasi 2015) , rough set theory (Kobayashi & Niwa 2018; Kuramaru, Takanashi & Mori 2001; Ohki, Harada & Inuguchi 2012; Pawlak 1982; Yamada, Moroga & Uehara 2012), self-organizing map (Kobayashi & Niwa 2018), etc. are used to analyze the relationships between the results of customers' Kansei evaluation of existing products and their aesthetic features. In addition, with the recent development of deep learning, methods using deep learning have also been proposed. Ota et. al. proposed Kansei retrieval system to search for user's favorite clothing based on CNN and ANN (Ota, Takenouchi & Tokumaru 2017). Quan, Li and Hu (2017) proposed the Kansei engineering-based neural style transfer for product innovation (KENPI) framework. Dai, Li and Liu (2019) proposed the approach for automatic design scheme generation based on GAN (Goodfellow et. al. 2014). Schmitt and Weiss (2019) designed innovative chairs inspired by the chair images generated by GAN.

In this study, A GAN-based design method that generates new products from the images of the customer's favorite products is proposed. In the proposed method, the product images that customers evaluated as preferable are used as the training set of GAN. If the GAN fulfills its capabilities properly, the images generated from a customer's favorite product are more likely to be preferred by the customer. In the case study, the proposed method was applied to chair design. The generated chair images were first evaluated in terms of image quality, i.e., whether they looked like chairs or not, and how innovative they were compared to existing chairs, and then evaluated by subjects in terms of their preferences.

2 GAN

Generative Adversarial Network (GAN) were first proposed by Goodfellow et al. (2014). It contains two networks: one is a generator, and the other is a discriminator. The purpose of the generator is to learn to capture the statistical distribution of training data, to make samples from the learned distribution, and to make realistic images. The discriminator is intended to receive both composite samples and actual images and to distinguish them. As the generator and the discriminator are trained simultaneously and compete with each other, the generator is able to produce images that are indistinguishable from the training data to human eye.

Since GAN is one of the hottest topics in the research field of machine learning and various types of improved GANs, such as Cycle GAN, ProGAN (Progressive GAN) and Style GAN have been proposed to improve the quality of generated images and GANs have been applied in a wide range of research fields.

3 PROPOSED METHOD

The proposed method consists of the following steps. Their details are explained in the following sections.

Step.1	Collection of training data
Step.2	Questionnaire investigation
Step.3	Image generation using GAN
Step.4	Super resolution using SRGAN

3.1 Step.1 Collection of training data

Images of existing products of the same type as the design target are collected. To avoid affecting the training results of GAN, only images in which the products are arranged in the same orientation are collected, background of the images is retouched to white, and the images are resized to the same size.

3.2 Step.2 Questionnaire investigation

A questionnaire investigation is conducted to collect information on customer's preferences, or likes/dislikes, for product images prepared in Step.1.

3.3 Step.3 Image generation using GAN

GAN is performed using only the product images that the customer rated as "like". Any GAN methods can be used, but Style GAN is used in this study. The time required to train a GAN depends on the number of training data and the image resolution but is generally very long. In this study, low-resolution images of 64*64 are used due to limited computer resources and time available for computation. Instead of using low-resolution images, super-resolution of the generated images is performed in the next step. If there are no constraints on computer resources and time available for computation, a high-resolution image can be generated directly, and the next step can be omitted.

3.4 Step.4 Super resolution using SRGAN

The low-resolution generated images are super-resolved to high-resolution images. Any super resolution methods can be used, but SRGAN (Ledig et. al. 2016) is used in this study. High-resolution images of products of the same type as the design target are collected and used as training data for SRGAN. By using only product images of the same type as the design target, it is expected to produce a high-resolution image that well reproduces the characteristics of the same type of product being designed.

4 CASE STUDY

In order to examine the effectiveness of the proposed method, the proposed method was applied to chair design. Six undergraduate students participated as subjects. Because everyone has different preferences for products, the results of the six questionnaires were processed individually.

4.1 Step.1 and 2

4735 photos of chairs were collected from Google Image. The chairs in the images were oriented in the same direction and the background of the images was changed to white. Figure 1 shows examples of prepared chair images.

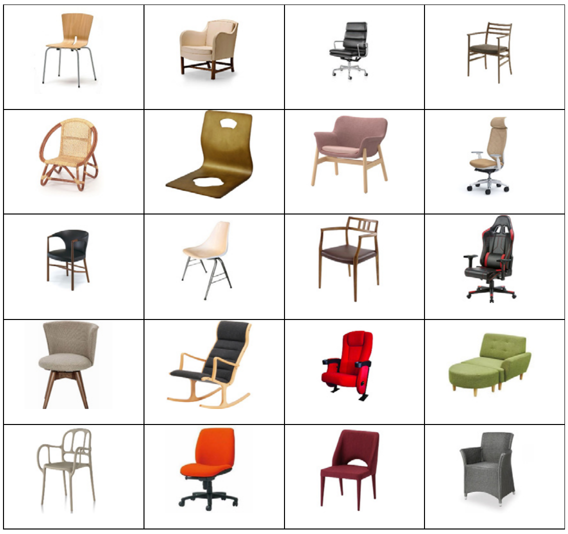

Figure 1. Examples of prepared chairs

Six subjects then rated their likes / dislikes of the collected chairs. Since GAN requires a very large amount of training data, i.e., preferences for product images, the survey system shown in Figure 2 was constructed in order to reduce the load on the subjects. The program randomly presents product images and allows subjects to enter "like" or "dislike" by two keys on the keyboard. Table 1 shows the questionnaire results.

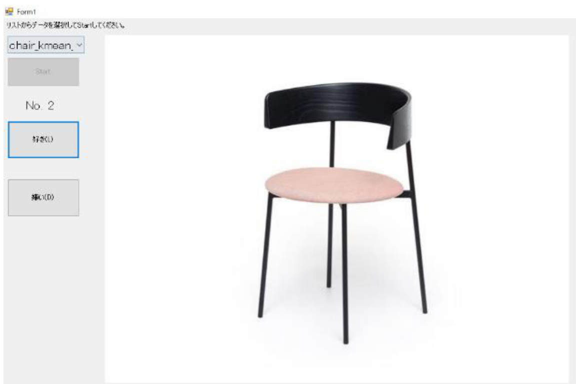

Figure 2. Survey system

Table 1. questionnaire results

Subjects	# of liked chairs	Percentage of liked chairs
1	1762	37.19%
2	2324	49.08%
3	1491	31.49%

4	3904	82.45%
5	1655	34.95%
6	1710	36.11%

4.2 Step.3 and 4

GAN was performed using only the product images that the customer rated as "like". Figure 3 shows the examples of generated chairs. 216 images were generated for each subject.

Figure 3. Examples of generated chairs

Generated images were then super resolved by using SRGAN. Figure 4 shows the examples of super resolved images. For comparison, the images upscaled by the traditional bicubic method were included in the figure.

Figure 4. Examples of super resolved images

4.3 Discussion

Obtained chair images were first evaluated in terms of image quality. Specifically, the obtained chair images are classified into the following four groups: New style of chairs, Normal chairs (same as training data), Unbalanced chairs (chairs without some parts), Not chairs. This classification was done manually by the authors. Figure 4 shows the chair examples of 4 groups. Table 2 shows the percentage of chairs belonging to each group.

Figure 4. Classification of obtained chairs

Table 3. Results of classification

Group	Percentage of chairs
New style	26.81%
Normal	47.66%
Unbalanced	5.53%
Not a chair	20.00%

Then, 20 chair images were randomly selected from those judged as new for each subject and they rated their likes / dislikes of those chairs. Table 3 shows their results. These results indicate that subjects are more likely to prefer chair images generated using images of their favorite chairs as training data than the images of randomly collected chairs. In other words, GAN generates images by capturing the characteristics of customer preferences. One concern in judging the validity of the results is the limited image resolution due to a processing capability problem. Such low-resolution images can represent the overall form of the chair, its structure, and its color, but they cannot represent detailed designs, such as fabric patterns and textures, or small parts. However, there are situations where customers rate their like / dislike for products using low-resolution images, e.g., when they are browsing the Web for a new chair. In such situation, the results are reasonable.

Table 3. Results of subjects' rating

Subjects	Percentage of liked chairs (obtained)	Percentage of liked chairs (original)
1	85%	37.19%
2	80%	49.08%
3	60%	31.49%
4	65%	82.45%
5	30%	34.95%
6	65%	36.11%

5 CONCLUSION

To design products that customers prefer based on the results of their kansei evaluations of existing products, a GAN-based design method was proposed. In the case study, the proposed method was applied to chair design. Chairs designed using the proposed method have a higher probability of being preferred by customers than randomly collected chairs. This result indicates that the proposed method designs products by the characteristics of customer preferences.

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