Title:
Design Generation Using Stable Diffusion and Questionnaire Survey

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Keywords:
Kansei Engineering, Aesthetic Design, Deep Learning, Stable Diffusion

DOI: 10.14733/cadconfP.2023.226-231

Introduction:
Due to the maturation of science and technology, it becomes increasingly difficult to differentiate products in terms of performance, functional features, or price. Therefore, companies are required to differentiate their products in terms of subjective and abstract qualities such as aesthetics and comfort that are evaluated by customers' feelings, which is called “Kansei” in Japanese. The quality evaluated by customer Kansei is called “Kansei quality”.

In the field of Kansei engineering (referred to as affective or emotional engineering), the methods for measuring customer Kansei or the impression of products have been developed and applied to many case studies. In these methods, semantic differential (SD) method [8] is widely used. Based on the measurement and analysis methods of customer Kansei, various aesthetic design methods have also been developed. These methods generate a new aesthetic design that a customer prefers best by revealing the relationships between the results of customers’ Kansei evaluation of the same type of existing products as the design target and their aesthetic features. In these methods, various analysis methods such as artificial neural network [4] [5], fuzzy set theory [3], interactive reduct evolutionary computation [18], multidimensional scaling [5], rough set theory [6] [8-9] [11] [17], self-organizing map [5], etc. are used.

In recent years, deep learning is attracting a lot of attention. Deep learning is a class of machine learning algorithms based on artificial neural networks. Deep learning uses multiple layers to extract higher-level features progressively and automatically from the raw input. In the case of image classification, lower layers may identify edges, while higher layers may identify the concepts relevant to a human such as digits, letters, or faces. Various types of deep learning models have been developed and applied to computer vision, speech recognition, natural language processing, audio recognition, self-driving car, board game, etc. Deep learning has also been used in research on Kansei engineering. For example, Quan et. al. proposed the Knsei engineering-based neural style transfer for product innovation (KENPI) framework [12]. Dai et. al. proposed the approach for automatic design scheme generation based on generative adversarial networks (GAN)[1][2]. Schmitt and Weiss designed innovative chairs inspired by the chair images generated by GAN [15]. Kobayashi et al. confirmed that product images generated using GAN with only product images that customers preferred as input were highly likely to be preferred by customers [6].

In 2022, Stable Diffusion [16], another deep learning-based image generation method, has been proposed and has attracted much attention. Stable Diffusion uses a variant of diffusion model (DM), called latent diffusion model (LDM) and generates detailed images conditioned on text descriptions called “Prompt”. By inputting appropriate text description as prompts, Stable Diffusion can generate a variety of images, including fictional animals that look like a mixture of real animals, detailed images indistinguishable from actual photographs, and cartoon-like illustrations.

In this research, a new method for generating product designs based on Stable Diffusion and questionnaire surveys. A little more specific, to generate a product design with certain impressions, Kansei words representing those impressions are input to Stable diffusion as prompts. To identify the customer's preferences and the impressions that the customer wants the product to have, and to generate the most favorable product design, questionnaire surveys are combined with stable diffusion. Then, questionnaire surveys are conducted to identify what impression the customers want the product to have and what kind of product they prefer. Based on the results, fine tuning called “embedding” is performed in Stable diffusion to generate images of products that customers would most likely prefer. In the case study, the proposed method is applied to a chair design to verify whether it is possible to generate product designs that give specific impressions to subjects and whether it is possible to generate product designs that subjects prefer.

Proposed method:

The proposed method consists of the following 4 steps.

Step1: Generation of product images with specific impressions
Step2: Verification of customer impressions of the products through questionnaire surveys
Step3: Evaluation of customer preferences for the products through questionnaire surveys
Step4: Fine tuning and product image generation

Step1: Generation of product images with specific impressions

In Step 1, product images for the questionnaire surveys in Steps 2 and 3 are generated by giving prompts to Stable Diffusion. The prompts that input into stable diffusion are the words that describe the target product, e.g., “chair” or “office desk”, and the Kansei words that describe the impressions that the product should have, e.g., “soft” or “gorgeous”. For the Kansei words, pairs of Kansei words that are suitable for describing the target product, e.g., hard-soft, are collected and combined for the prompt. In the example, four pairs of Kansei words are collected and two of them are combined. Product images are generated for all combinations of Kansei words except for paired, conflicting Kansei words. Multiple images are generated for each prompt.

Step2: Verification of customer impressions of the products through questionnaire surveys

A questionnaire survey is conducted to confirm whether the product images generated in Step 1 are as impressive as the prompts. In the questionnaire, the product images are rated on a 5-point scale using Kansei words that are given as the prompts. The questionnaire results are analyzed and if the product images generated have the impressions as prompted, then go to the next step. If not, return to Step 1 and product images should be re-generated. In this case, it is advisable to change the Kansei words to synonyms, add words that identify the part to which the Kansei words applies, or increase the number of words that describe the target product.

Step3: Evaluation of customer preferences for the products through questionnaire surveys

Questionnaire surveys are conducted to measure the preference for the product images generated in step 1 and validated in step 2. Preference for the product images is rated on a 5-point scale.

Step4: Fine tuning and product image generation

Product images are selected in the following two ways.

(a) The average score of the preference is calculated for each group of product images with the same prompt, and the images of the group with the highest preference are selected.

(b) Product images with a 5 rating on a 5-point scale of preference are selected, regardless of their group.

Fine tuning, called embedding, is then performed using these images to generate product images that reflect the subject's preferences.

Case study:

To confirm the effectiveness of the proposed method, it is applied to a chair design. 4 male undergraduates participated as subjects. The proposed was applied to each subject individually. Eight Kansei words or four pairs of Kansei words (round/square, cool/cute, luxury/simple, and soft/hard) were used to describe the impression of the chair. Two of these eight Kansei words were selected for each prompt. Since conflicting combinations (e.g., round/square) were excluded, 24 combinations were possible. These combinations were named Groups 1-24. Kansei words used for each group are listed in

Tab.1. As for the words for chair, “chair” was used. To obtain a better chair image, “round” and “square” were described as "has a wound back and seat". "soft" and "hard" were described as "made by soft material". 10 product images were generated for each group. Some of the generated images are shown in the Fig.1.

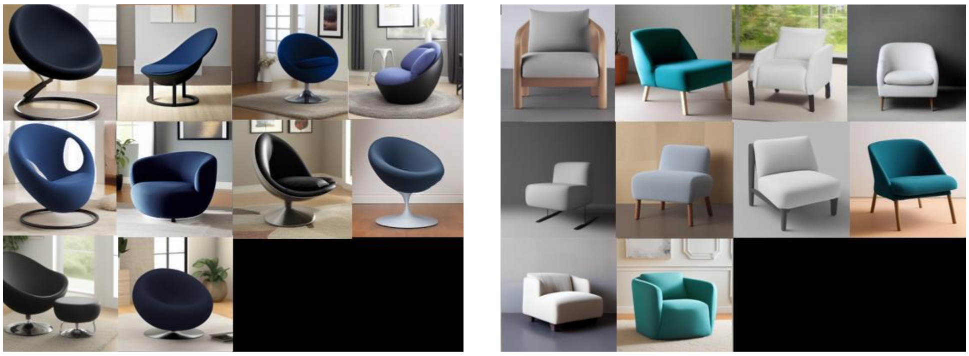

Fig. 1: Generated chair images (Left: round & cool, Right: simple & soft).

A first questionnaire survey was conducted on these chair images. Tab.1 shows the questionnaire results. This table shows that Kansei words and average score for each group. This table confirms that the use of Kansei words as prompts can generate the product image with specific impressions.

Group	1	2	3	4	5	6	7	8	9	10	11	12
Kansei words	round cool	round cute	round luxury	round simple	round hard	round soft	square cool	square cute	square luxury	square simple	square hard	square soft
Average score	4.68	4.69	4.23	4.56	4.25	4.75	3.71	3.65	3.85	4.76	4.78	3.93

13	14	15	16	17	18	19	20	21	22	23	24
cool luxury	cool simple	cool hard	cool soft	cute luxury	cute simple	cute hard	cute soft	luxury hard	luxury soft	simple hard	simple soft
4.24	4.26	4.38	3.84	4.56	4.1	4.43	4.68	3.83	4.63	4.71	4.53

Tab. 1: Questionnaire results.

A second questionnaire was then conducted to measure the preference for these chairs. Tab.2 shows the groups with the higher average scores for the preferences. The table shows that each subject has different preferences.

	Subject1		Subject2		Subject3		Subject4	
Rank	Group	Average score	Group	Average score	Group	Average score	Group	Average score
1	13	4.6	22	5	22	4.8	3	5
2	24	4.4	16, 13, 3	4.6	24	4.5	1	4.7
3	1	4.3			13, 17	4.4	6, 14, 24	4.6

Tab. 2: Questionnaire results.

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Finally, the product images were selected in the ways described in (a) and (b) of Step 4. In method (a), images from the rank 1 group shown in Tab.2 were selected. In method (b), images with a score of 5 were selected. The number of images selected by method (b) was 28 for subject 1, 79 for subject 2, 47 for subject 3, and 79 for subject 4. Fine tuning was finally performed using these images. Examples of chair images generated for each subject are shown in Fig2.

Fig. 2: Created chair images (Left: Subject1 & method (a), Right: Subject1 & method (b)).

Discussion

The impressions that the subject received from the chair images generated for each subject and preferences for them were measured by questionnaire survey. Tab.3 shows the results. This table shows the average scores for the 20 generated images for each condition.

	Subject1		Subject2		Subject3		Subject4	
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
Preference	4.4	3.9	4.7	4.9	4.8	4.9	3.1	3
Cute	2.4	1.5	4.5	4.8	4	2.3	3.4	3.5
Cool	4.2	4.5	1.5	1.2	2	3.7	2.6	2.5
Square	1.7	2.5	1.7	1.5	1.6	1.8	1	1.3
Round	4.3	3.5	4.3	4.5	4.4	4.2	5	4.7
Simple	1.6	2.1	1	4.1	1	2.9	1.3	4.2
Luxury	4.4	3.9	5	1.9	5	3.1	4.7	1.8
Soft	4.5	3.8	5	4.7	5	5	4.9	3.4
Hard	1.5	2.2	1	1.3	1	1	1.1	2.6

Tab. 3: Again, short captions should be centered under each table.

When focusing on preferences, the results show that both methods (a) and (b) can generate the product images preferred by the subject. When focusing on the impressions received from the product, the results show that the image generated after fine-tuning with method (a) has the same impression as the image of the group used for fine-tuning. On the other hand, in method (b), the subject's preference is the only factor to be considered when selecting images for fine tuning, so the impressions of the selected images are diverse. Therefore, the impressions of the images generated after fine tuning are also diverse. The method (a) is considered to identify impressions that are closely related to the customer's preferences first, and then to generate product images with the same impressions. On the other hand, method (b) is considered to use the customer's favorite product for fine tuning to allow Stable Diffusion to learn the customer's favorite design elements and then to generate products that include those elements. Therefore, despite the high preference for the generated images, their impressions are diverse. Either way, the results show that the proposed method can generate product images preferred by subjects using Stable Diffusion.

Conclusion:

In this research, a new method for generating product images using stable diffusion, which has been attracting attention in recent years, is proposed. By combining stable diffusion and questionnaire surveys, the proposed method can generate products that have specific impressions and that customers prefer from texts called prompts. In the case study, the effectiveness of the proposed method is demonstrated by applying it to the chair design.

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