Title:
Aesthetic Design Based on the Analysis of Questionnaire Results Using Deep Learning Techniques

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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 [7] 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 [16], multidimensional scaling [5], rough set theory [6-8] [10] [15], 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 researches on Kansei engineering. For example, Quan et. al. proposed the Knsei engineering-based neural style transfer for product innovation (KENPI) framework [11]. 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 [14].

In this paper, a new aesthetic design method that generates new designs that customers prefer by analyzing customer's preferences using deep learning methods is proposed. More specifically, aesthetic elements that are closely related to the customer's “like” evaluations are identified by analyzing the CNN network that learns the relationships between images of existing products and customer’s preferences for those products collected from questionnaire investigations. Here, an aesthetic element is defined as a part of a product from the viewpoint of product aesthetics. For example, "backrest", "seat", "armrest", and "leg" are aesthetic elements of a chair. New designs are then generated by combining the collected elements.

Proposed Method:

The proposed method consists of the following 4 steps. Their details are explained in the rest of this section.

Step1: Investigation of customer's preferences using questionnaires
Step2: Leaning of customer's preferences using CNN
Step3: Analysis of customer's preferences using Grad-CAM
Step4: Generation of new designs

Step1: Investigation of customer's preferences using questionnaires

The first step is to collect customer's preferences for existing products through questionnaire investigations. Since training a CNN requires a large amount of training data, e.g., thousands, the questionnaire program shown in Fig.1 is constructed in order to reduce the load on the subjects, in the case study of this paper. The program randomly presents prepared product images and allows the subject to enter the liking or disliking by two keys on the keyboard.

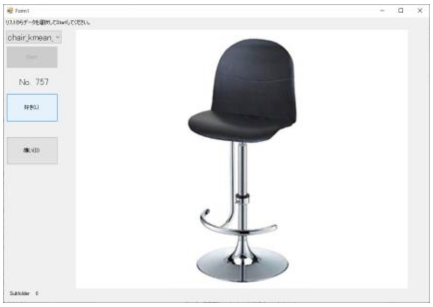

Fig. 1: Questionnaire program.

Step2: Leaning of customer's preferences using CNN

The relationships between images of existing products and customer's preferences for their products collected in step1 are learned by using a CNN. CNNs are often used for image classification tasks such as classifying an animal in an image as a dog or a cat. In the proposed method, a CNN learns customer's preferences (like or dislike) for existing products and infers customer's preferences for unknown products. Various types of CNN models have been proposed and any of them can be used in this step. In the case study of this paper, a relatively simple CNN model consisting of 4 convolution layers and 2 max pooling layers is used.

When subjects are asked to evaluate their preferences for a large number of product images, as in this study, the accuracy and reliability of the questionnaire results may be insufficient. Therefore, the accuracy of the trained network is verified and if the accuracy is low, the subject is asked to re-evaluate the questionnaire investigations.

Step3: Analysis of customer's preferences using Grad-CAM

Using Grad-CAM and semantic segmentation, aesthetic elements that are closely related to the customer's "like" evaluations are identified and collected from images of the customer's favorite products.

Grad-CAM is a technique for producing 'visual explanations' for decisions from a large class of CNN-based models, making them more transparent and explainable [13]. CNNs have been successfully applied to a wide variety of computer vision tasks, such as image classification, object detection, semantic segmentation (image captioning, visual question answering, visual dialog, and embodied question answering). The most critical problem for using CNNs is difficulty in understanding why the system did what it did. Therefore, various types of 'visual explanation' techniques that reveal what the CNN focused on in the input image to make its inference by analyzing the trained network have been proposed. In the proposed method, Grad-CAM is used.

Semantic segmentation is the task of clustering each pixel in an image together which belongs to the same object class. In the proposed method, semantic segmentation is used to identify aesthetic elements from product images. For example, it recognizes the backrest, seat, elbows, and legs from an image of a chair. Various types of semantic segmentation methods have been proposed. In the case study of this paper, U-Net [12] is used.

The detailed procedure of Step3 is as follows. (1) Using Grad-CAM, what part of images of the customer’s favorite products is related to the customer’s preference is analyzed. Since Grad-CAM calculates the effect of each pixel in an image on the inference result, the relationships between aesthetic elements and customer's preferences are not yet identified. (2) Using U-Net, aesthetic elements are identified from images of the customer’s favorite products. (3) From the results of Grad-CAM and semantic segmentation, aesthetic elements that are closely related to the customer's “like” evaluations are identified. They are cut out from the product images and collected. There are cases multiple aesthetic elements are closely related to the customer's preferences at the same time. In such cases, multiple aesthetic elements are cut out together. This is because there is a possibility that a combination of multiple aesthetic elements contributes to the customer's “like” evaluations whereas individual elements don’t due to combination effects in an aesthetic design.

Step4: Generation of new designs

Finally, new product designs are generated by combining customer’s favorite aesthetic elements collected in Step3. Generated designs are evaluated by the CNN and Grad-CAM. The CNN infers whether a customer prefers the entire design whereas the Grad-CAM analyzes whether a customer prefers each part of the design.

Case Study:

To show the flow of the proposed method, it was applied to the design of the chair. The design targets were a wide variety of chairs such as office chairs, dining chairs, and sofas. The subject was a man in his early twenties.

First, chair images for the questionnaire investigation were collected from the Internet. Only chairs with the same orientation were selected from them and the background of the chairs was changed to white using photo-retouching software. 4684 chair images were prepared. Fig.2 shows their examples.

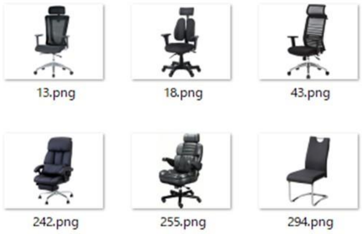

Fig. 2: Examples of chair images.

A subject was asked to evaluate his preferences of 4736 chairs using a questionnaire program shown in Fig.1.

A CNN network was then trained using chair images and questionnaire results. As described above, the CNN network used in the case study consisted of 4 convolution layers and 2 max pooling layers. 75% of training data was used for training and 25% for validation. The accuracy of the trained CNN was 81.3%. This is worse than expected. This is probably because the subject was required to evaluate a very large number of questionnaires, which made it difficult to evaluate them consistently.

The chairs that the customer evaluated as "like" were analyzed by using Grad-CAM. Fig. 3 shows examples of the results of Grad-CAM. The redder the pixel in the image, the more relevant it is to the customer's "like" evaluation. As shown in Fig.3, there are also cases where the analysis cannot be done well.

Fig. 3: Examples of the results of Grad-CAM.

Next, the U-Net network was trained to identify aesthetic elements from images of the customer’s favorite products using semantic segmentation. For training the network, 1000 training data as shown in Fig.4 were manually prepared in advance. In the case study, a chair is divided into 3 elements namely "backrest & seat", "armrests", and "leg". Using the trained network, semantic segmentation was applied to the customer's favorite products and the results were compared with the results of Grad-CAM. Fig.5 shows examples of the results of semantic segmentation and Grad-CAM. By comparing these two images, it becomes clear which aesthetic elements of the chair are closely related to the customer's "like" evaluation. This series of operations was applied to multiple product images to collect candidates for aesthetic elements to be used in Step 4.

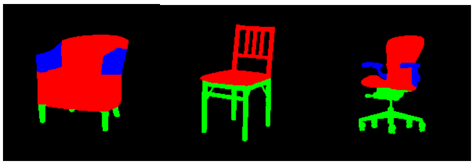

Fig. 4: Examples of training data for semantic segmentation.

Fig. 5: Comparison of the results of Grad-CAM and semantic segmentation.

Finally, 10 new designs were generated by combining the aesthetic parts and evaluated using CNN and Grad-CAM. Fig.6 shows examples of the generated design and evaluation results. The subject was asked to evaluate the generated designs for confirmation, and he evaluated 9 out of 10 products as "like".

Fig. 6: Examples of the generated chair designs.

These results show that the proposed method can generate new designs that customers prefer from the results of questionnaires on existing products.

Conclusion:

In order to generate new designs that customers prefer from the results of questionnaires on existing products, a new aesthetic design method using on CNN and Grad-CAM. In the proposed method, Grad-CAM calculates the effect of each pixel in an image on a customer's "like" evaluation by analyzing the CNN network that learns customer preferences. Semantic segmentation then identifies aesthetic elements from product images. By comparing two results, the aesthetic elements that affect customer's "like" evaluation are be clarified. Therefore, by collecting and combining their parts, new designs that customers prefer are generated. In the case study, the proposed method was applied to chair design, and its effectiveness was confirmed.

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