Kansei Modeling on Visual Impression from Small Datasets

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Abstract. Large datasets are generally required for machine learning. In order to improve the efficiency of the system, our team proposes a new Kansei modeling method, which requires users to collect only a small dataset. Using our method, the small datasets can search and collect large datasets classified in detail. As a result, our method creates the well-tuned Kansei model only from small datasets without the trouble of collecting many datasets.

Keywords: Kansei Modeling, Machine Learning, Image Retrieval System.

1 Introduction and Problems

Impressions and feelings evoked by an image vary depending on who is looking at it. In the image search by keywords, the same result is presented to any users and it is difficult to retrieve an image suitable for each user's impression. Our team has been researching the Kansei modeling, a computational modeling of visual impression process, for scenery photos to retrieve an image suitable for each user [1].

In the earlier study for the Kansei model, our team analyzed the relation between information given in the photo and users' evaluation based on the visual impression using discriminant analysis [1]. However, this previous methods had the following problems, placing a large burden to the users.

(A) Detailed classification of datasets: Users train the system by providing classified datasets with impression words. However, because impression is something subjective for the users, dispersions of image features of the impression data tend to become larger. This results in lower modeling accuracy. Therefore, training datasets for modeling requires detailed classification in order to avoid this problem.

(B) Preparation of large datasets: Generally, when data prepared is small for machine learning, modeling accuracy gets lower. Therefore, users must prepare large datasets for machine learning.

For the reasons stated above, we propose a new Kansei model method, which requires only small dataset classified roughly. The problems can be solved by detailed classification and a searching system that automatically collects similar datasets based on image features of training data provided by the user. This method will greatly decrease the users' load.

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2 Solution

2.1 Detailed Classification of Datasets

To solve the problem identified in Chapter 1 (A), we propose a method of subdividing datasets by K-means. This method is effective for machine learning because subdividing datasets decreases dispersion of data sets and increases the modeling accuracy.

For K-means, the number of clusters needs to be specified. For our research, the number of clusters was set so that correlation ratio is maximized. The correlation ratio η is defined by the following expression.

$$\eta = 1 - \frac{|S_w|}{|S_T|}$$

S_W means within-groups sum of squares and products matrix. S_T means total sum of squares and products matrix.

2.2 Preparation of Large Datasets

To solve the problem described in Chapter 1 (B), we propose a method of automatically searching large impression image datasets, which share common characteristics with the small data provided. As a result, large datasets can be prepared just by small datasets given, and machine learning can create a model with high accuracy.

When users subjectively judge the degree of similarity of images, the users do not equally evaluate each characteristic in the image or weigh values that users stress [2]. Therefore, the similar images need to be searched by taking into account users' different attention degrees to various image features.

We assumed that we can measure the extent of users' consistency in selection criteria by assessing dispersion in the distribution of users' values on image characteristics. We also assumed that as the distribution is more dispersed, the users' selection criteria become inconsistent or that the users do not focus on particular values. Conversely, as the dispersion narrows, the users' selection criteria become consistent, or the users focus on the certain values.

The images below show search results obtained by estimating characteristics that users focus on from a few sample images.

(a) Search key (b) Search results

Fig. 1. Example of searching images by estimating characteristics that users stress from a few sample images

3 Experiment to Evaluate Search System

This experiment verified the accuracy of our image search system, which estimates image characteristics that users focus on in accordance with detailed classification of datasets.

In the experiment, we used a database comprised of approximately 1,725 landscape images taken by a professional photographer. Impression words were assigned to each landscape image. Each impression word had the following number of images as shown in Table 1.

Table 1. Number of images for each impression words in experiment

Impression words	Number of images
Fresh	436
Natural	437
Modern・Classic	430
Elegant	422

First, the search system randomly selected 10, 20, and 30 traning image data for each impression word above from all the experimental images. Then, in order to verify the accuracy of the search system, we examined the top 200 search results based on the training data and calculated the conformity level between pre-assigned impression words and results' impression words. The experiments were repeated 20 times. The average value of the conformity level is shown in Fig.2.

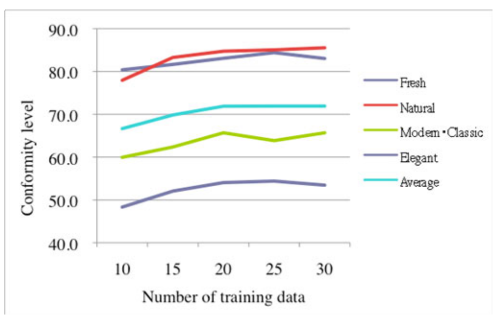

Fig. 2. Relation between the number of data sets and conformity level

The conformity level went up when the number of data sets increased (Fig.2). Also, the results of 'Fresh' and 'Natural' kept high accuracy because the resulting colors and textures were similar for each of those two impression words; data sets of 'Fresh' had images of sky and ocean, and 'Natural' had images of forest and mountain. Therefore, our system could easily search suitable images that share the same characteristics as the training data.

Conversely, the results of 'Modern・Classic' and 'Elegant' had low accuracy. Training datasets of 'Modern・Classic' and 'Elegant' all had similar images such as buildings and night scene. Accordingly, the resulting colors and textures among those impression words were similar without clear difference. Because our system could not evaluate impression well for those impression words lowering the conformity level, we must reconsider the amount of characteristics to input so that the system can evaluate images correctly.

4 Experiment to Evaluate Kansei Modeling

We create Kansei model with SVM (Support Vector Machine) to evaluate user's Kansei quantitatively. This experiment verified the accuracy of our Kansei modeling using image data searched by our system. We created four types of Kansei model by using 200 datasets for each. The datasets were three combinations of 10, 20, 30 training datasets and complementary search results in the previous experiment (Chapter 4) and 200 datasets selected randomly without using our search system. The conformity level for each model is shown in Table 2.

Table 2. Relation between number of search results and the conformity level

Training Data Search Result	10 190	20 180	30 170	200 0
Fresh	89.6%	85.2%	83.1%	91.0%
Natural	86.0%	90.8%	84.8%	95.0%
Classic・Modern	62.1%	65.6%	66.0%	72.5%
Elegant	51.7%	49.0%	49.4%	63.5%
Average	72.3%	72.7%	70.8%	80.5%

According to Table 2, our proposed system can create Kansei model by a small dataset at the same or a little lower level of the model obtained from 200 training data sets. However, the accuracy of model for 'Classic・Modern' and 'Elegant' obtained from search results was especially lower than the model from 200 training datasets. This low accuracy occurred because the images came from the search result in the previous experiment, which could not find adequately suitable image for impression words of 'Classic・Modern' and 'Elegant' (Chapter4).

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