Title:
Product recommendation based on analysis of aesthetic elements used to customer's favorite products

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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".

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. In addition, various aesthetic design methods based on analysis of measured customer kansei have also been developed. These methods generate a new aesthetic design which 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 method, various analysis methods such as artificial neural network [2] [3], fuzzy set theory [1], interactive reduct evolutionary computation [10], multi-dimensional scaling [1], rough set theory [4-6] [8] [9], self-organizing map [3] etc. are used.

In recent years, recommendation systems have been widely used for product recommendation at EC sites and so on. Existing recommendation systems are mainly based on cooperative filtering, but this approach simply estimates the customer preferences from the information about other customers with similar purchase histories and doesn't take into account customer kansei, i.e., the degree of the impressions and preferences that they receive from the product, the design / aesthetic features of the product, and their corresponding relationships. For more accurate estimation of customer preferences, a new recommender system that considers customer kansei is proposed in this paper. required. The proposed system makes product recommendations by collecting information about the many different types of products that customers have purchased or preferred in the past and analyzing the correspondence relationships between the customer preferences and their design / aesthetics.

Proposed method:
Before explaining the proposed system, three technical terms are introduced here. "Aesthetic element" is a part of product design / aesthetic. Examples of aesthetic elements are "blue", "red", "metal", "leather", "zipper" and "button". Products consist of various aesthetic elements. "Aesthetic element type" is a set of similar aesthetic elements. Examples are "color", "material" and "fastener". Each aesthetic element type has several aesthetic elements as its option. For example, "blue" and "red" are options of "color" type. "Product type" is a set of products having same types of aesthetic elements.

Examples of product types are “sneaker” and “backpack”. In addition to the introduction of three technical terms, two parameters are also introduced. The first parameter is “similarity” of aesthetic element types between different product types. For example, since the colors of bag and wallet are quite similar, the customer's color preference of bag color can be estimated from the customer's color preference of wallet. In such case, “similarity” of color between bag and wallet becomes high. Fig.1 illustrates the concept of "similarity" between 2 product types. The second one is “priority” of aesthetic elements. Generally, products consist of many types of aesthetic elements. Some aesthetic elements have a great impact on customer’s preference while others have a small impact on customer’s preference. Therefore, degree of their impact is defined as “priority”.

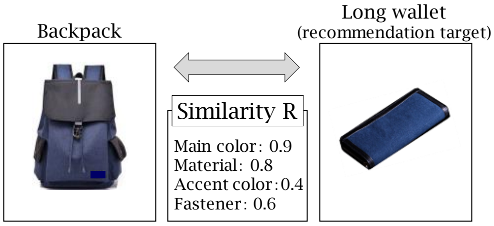

Fig. 1: Concept of "similarity" between 2 product types.

The proposed method consists of advance preparation + 2 Steps. The rest of this section explains their details.

Advance preparation: Data collection

In order to make product recommendations using the propose system, it is necessary to collet as much information as possible about customer’s favorite products. A customer has considered purchasing a variety of products in the past. Therefore, the products preferred by a customer are recorded at that time. The more records collected, the more accurately customer preferences can be estimated. At least, all aesthetic elements used in the candidate products for recommendation must be included in one of the recorded customer’s favorite products. In the case study, since there is no information on customer’s favorite products, subjects selected 3 favorite products out of 20 products for each of 6 product types by means of a questionnaire investigation.

Step1: Calculation of contribution score

In step1, contribution of aesthetic elements used in candidate products for recommendation to customer’s preference is separately calculated. As described before, the basic concept of customer preference estimation is that aesthetic elements frequently used in various types of customer’s favorite products are closely related to customer’s preference. Based on this concept, contribution is calculated separately for all aesthetic elements that make up candidate products by the below equation. When the candidate product type consists of n aesthetic elements and information about customer’s favorite products belonging to l product types are used for estimation, contribution score $S_{i,j}$ of aesthetic element i that belongs to aesthetic element type j is calculated by the below equations.

$$C_{i,j} = \sum_{k=1}^{l} N_{i,k} \times R_{j,k}$$

$$\text{Contribution score } S_{i,j} = \frac{W_j \times C_{i,j}}{\max_i C_{i,j}}$$

Where, $N_{i,k}$ is the number of times aesthetic elements i is used in the customer's favorite products belonging to product type k. $R_{j,k}$ is the similarity of aesthetic element type j between the candidate product type and product type k. W_j is the priority of aesthetic element type j. max $C_{i,j}$ is the largest C of aesthetic elements that belong to aesthetic element type j. This term is used for normalization.

Step2: Estimation of customer's preference for candidate products

Customer's preference of candidate products is estimated by summing up contribution score of aesthetic elements that make up them. Customer's preference P_l of candidate product l is calculated by the below equation.

$$\text{Preference score } P_l = \frac{\sum_{j=1}^{n} S_{i,j} \in product\ l}{\sum_{j=1}^{n} \max_i S_{i,j}}$$

Where the numerator is the sum of contribution scores of the aesthetic elements that make up candidate product l. The denominator is the sum of the maximum contribution scores for each aesthetic element type. The preference scores are calculated for all candidate products and the candidate product with the highest preference score is recommended.

<u>Case study:</u>

To confirm the effectiveness of the proposed method, a case study was performed. Based on the information on 6 types of customer's favorite products: backpack, smartphone case, sneaker, pencil case, tie and scarf, a long wallet was recommended. 18 undergraduate students participated as subjects.

Preparation of the case studies

In order to collect information about customer's favorite products, 12 products (photos) were collected from each of 6 product type described above. 12 long wallets were also collected as candidate products. Participants selected 3 favorite products from each of 6 product types using questionnaire sheets illustrated in Fig.2. For discussion after the experiment, participants also select 3 favorite products from 12 long wallets. "Long wallet" type has 7 aesthetic element types (Main color, pattern, material, accent color, glossy, fastener type and zipper strap) while 6 product types have 3 to 5 aesthetic element types. Tab. 1 shows the aesthetic element types which 6 product types have. As for Similarity and priority, Tab.1 and 2 show similarity R between a long wallet and 6 product types and priority W among 7 aesthetic element types respectively. Note that pencil cases, like backpacks and smartphone cases, have zippers, but that information cannot be used to estimate customer preference because all products that belong to "pencil case" have zippers and no other options. Therefore, no information is listed in the fastener columns of Tab. 1.

Results and discussions

The contribution score for each design element is calculated from the information written in the previous section and the customer preferences of the candidate long wallets are estimated by summing the values. Tab. 3 shows the preference scores of candidate products of subject 1 and 2. This table also shows 3 favorite products pre-selected by subject 1 and 2. As for subject 1, 2 of 3 favorite products can be estimated by the proposed system while, as for subject2, no favorite products can be estimated. Tab. 4 shows how many favorite products the proposed system can estimate. These results show that the proposed system can recommend products based on past information on various types of customer's favorite products in a certain accuracy level. The problems of the proposed system and case study are as follows. (1) In the proposed system, similarity R and priority W need to be manually configured, but they may not have been configured appropriately in the case study. (2) Priority of aesthetic elements might have been better to be configured for each subject. This is because subjects have their own evaluation viewpoints when selecting favorite products.

Fig. 2: Example of questionnaire sheets.

	Main color	Pattern	Material	Accent color	Glossy	Fastener	Zipper strap
Backpack	0.9	-	0.8	0.4	0.6	0.6	-
Smartphone case	1	0.9	0.9	-	0.9	0.2	-
Sneaker	0.8	-	0.7	0.2	0.8	-	-
Pencil case	0.9	-	0.9	-	0.9	-	0.8
Tie	0.8	0.7	-	0.2	0.2	-	-
Scarf	0.6	0.7	-	0.4	-	-	-

Tab. 1: Similarity R of aesthetic elements between a long wallet and 6 product types.

Main color	Pattern	Material	Accent color	Glossy	Fastener	Zipper strap
1	0.8	0.9	0.3	0.3	0.6	0.2

Tab. 2: Priority W among 7 aesthetic element types.

<u>Conclusion:</u>

Different from product recommendation based on collaborative filtering like EC sites, a new stem that recommends products which a customer is most likely to prefers best by analyzing aesthetics of products which a customer evaluated as “favorite products” in the past. The proposed system takes aesthetics of candidate products for recommendation apart into aesthetic elements, calculate their contribution to customer’s preference from information on how often aesthetic elements are used in customer’s favorite products and estimates customer’s preference for candidate products. In the proposed system, once information on customer’s preference for various types of products are sufficiently collected, it becomes possible to recommend new types of products without additional information. In the case study, a long wallet was recommended based on information on customer’s preference for products belong to 6 product types. 18 subjects participated the case study. The results show that the proposed system can recommend products in a certain accuracy level.

As for future research, a method for configuring optimal values of similarity and priority needs to be considered.

ID of candidate products	Subject1		Subject2	
	Preference	Favorite products	Preference	Favorite products
1	67.1	✓	63.4	
2	54.3		85.7	
3	84.8	✓	70.7	✓
4	51.9		66.7	✓
5	90.0	✓	74.7	✓
6	69.9		72.9	
7	65.7		77.2	
8	71.2		79.7	
9	68.4		90.2	
10	76.3		77.8	
11	60.8		73.0	
12	57.0		86.4	

Tab.3: Results of subject 1 and 2.

# of correct estimation	# of subjects
3	0
2	7
1	8
0	3

Tab.4: Results of 18 subjects.

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