Association Rule Mining for Affective Product Design

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Abstract - **Affective product design implies a gradual shift of design focus from functional aspect to affective/emotional aspect. It evolves as an interdisciplinary research topic between human factors, industrial design and many other disciplines. This paper applies association rule mining to reveal the mapping relations between customer affective needs and configuration of design elements. Generic affective dimensions of truck cab were identified by clustering analysis. A goodness criterion was introduced to refine association rules. A case study of Volvo truck cab design was conducted based on the proposed methods.**

Keywords - **affective product design, association rule mining, conjoint analysis, clustering analysis**

I. INTRODUCTION

Today, satisfying customer needs has become a great concern of almost every company [1]. Among the whole spectrum of customer needs, functional and affective needs have been recognized to be of primary importance [2]. Traditional product design has focused on functional aspect of user needs, making products easy to understand, easy to handle and so forth [3]. However, affective needs, which emphasize on customers' emotional responses and aspirations, are arousing more and more attention in comparison to the functional needs [2, 4]. In this context, emotional performance may be considered as an extra quality enhancing the value of physical products and empowering the company a competitive edge.

The challenge of affective product design is to capture customers' affective needs, to define the relationship between the needs and product elements, and to explore the affective properties that products intend to communicate through their physical attributes.

Jiao et al. [5] proposed the general process of affective design (Fig.1). Two domains, customer domain and designer domain, are the primary actors. Each has their own interest and distinctive research issues are implied. Considering customer domain, for example, how to measure customers' affective responses and how to provide them with products which satisfy their emotions? On the other hand, for the designers, how to facilitate the handling of affective needs information and assist them to design better products?

This paper adopts a three-step approach to identify the affective dimensions of product design. After that, it applies association rule mining to discover the mapping between customer affect and perceptual design elements. The rest of the paper proceeds as follows. Section 2 presents the review of previous research. Section 3 defines the problem context of affective product design. Methodology of this study is described in section 4. In section 5, a case study of Volvo truck cabs design is reported based on the proposed method. Conclusion is drawn in section 6.

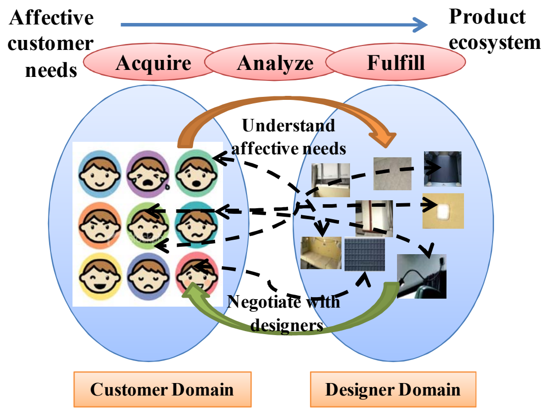


Fig.1. General process of affective design[5]

II. BACKGROUND REVIEW

Eliciting and measuring customer affect is known to be problematic. This is because affect is classified as "pleasure of the mind" and not accompanied by distinctive facial expressions [6]. Due to this reason, physiological measures which are widely used in Human Factors are not appropriate. Instead, subjective measures are adopted by most of the researchers. Osgood, Suci, & Tannenbaum [7] proposed semantic differential technique to analyze semantic structures and the affective meaning of things. Semantic differential technique has been successfully applied to find the semantic structure of designs, including the design of doors [8] , telephones[9], office chair [10] and so forth. The semantic environment description (SMB) was developed by Kuller [11] to evaluate the impression of an architectural environment. He validated 36 adjectives and grouped them into 7 factors. Karlsson, Aronsson & Svensson [12] applied Kuller's method for evaluation of car interior design. The results succeeded in discriminating among four passenger cars: BMW 318 (More complex and potent), Volvo S80 (More original and Higher social status), Audi A6 (Less enclosed) and VW Bora (Greater affect).

Upon understanding customer affect dimensions, mapping relations from customer affect to design elements can be extracted by qualitative and quantitative methods. Qualitative methods are simple. For example, focus group can be recruited to discuss the relationship. The reliability of their results, however, is usually upon further judgment of domain experts. Therefore, some researchers employed statistical methods of multivariate analysis, including multiple linear regression analysis [13], general linear model [14] and so on. These methods provide useful results but it has some theoretical limitation, for customer affect do not always have linear characteristics. To overcome this limitation, non-linear methods were proposed, including the quantification theory type I, II, III, and IV [15], genetic algorithm [16], neural networks [17] and others.

III. PROBLEM FORMULATION

As shown in Fig.1, affective needs are usually expressed by a set of affective descriptors $D = \{d_i| i=1,\ldots,n\}$. Due to the diversity of customers, it is imperative to conduct stratified sampling based on different market segments. Assuming there are several markets, $S = \{s_i| i=1,\ldots,I\}$, and each contains relatively homogenous customers, for customers in the i^{th} market segment, their affective needs can be described as a subset $D_i^* \subseteq D$. Meanwhile various perceptual product design elements are extracted from the designers. They can be characterized by another set $E = \{e_i| i=1,\ldots, m\}$. Each design element (factor) might have several levels. For example, the interior color (factor) of a truck cab can have three levels (blue, red, and grey). A possible combination of design elements with appropriate levels can be configured into a desired product.

III. METHODOLOGY

A. Elicitation and Measurement of Customer Affect

Helander & Tay [6] explored the possibility to use the same set of affective descriptors across different products and concluded that there were no universal affective dimensions for product design. Hence in this study, we follow a three stop approach to elicit driver affect of truck cab. The first step is to collect a large amount of affective descriptors that are representatives of consumer's feelings on a product. The list of descriptors can be generated from user interviews, related journals and magazines, and words used by marketing and design personnel In the second step, the most relevant and appropriate words are selected. The number of selected words varies from several dozens to several hundred. The selected words resulting from second step are clustered to identify the affective dimensions.

B. Association Rule Mining

Association rule mining is a well established data mining technique introduced by Agrawal & Srikant [18]. The basic goal is to find interesting relations between variables in large database. Two thresholds are required to measure an association rule—support and confidence. Support represents the frequency that items occur or co-occur in a transition record. Confidence represents the degree to describe how strong an item subset X implies another item subset Y. For the two domains in affective design, a general association rule can be formulated as follows:

$$d_i \,\&\, d_j \,\&\cdots\&\, d_k \Rightarrow e_i \,\&\, e_j \,\&\cdots\&\, e_k \tag{1}$$

where $d_i, d_j, d_k \in D, 1 \le i < j < k \le n$, and $e_i, e_j, e_k \in E, 1 \le i < j < k \le n$ based on the support and confidence thresholds:

$$s = \frac{Count(d_i \,\&\, d_j \,\&\cdots\&\, d_k \Rightarrow e_i \,\&\, e_j \,\&\cdots\&\, e_k)}{Count(DB)} \tag{2}$$

$$c = \frac{S(d_i \,\&\, d_j \,\&\cdots\&\, d_k \Rightarrow e_i \,\&\, e_j \,\&\cdots\&\, e_k)}{S(d_i \,\&\, d_j \,\&\cdots\&\, d_k)} = \frac{Count(d_i \,\&\, d_j \,\&\cdots\&\, d_k \Rightarrow e_i \,\&\, e_j \,\&\cdots\&\, e_k)}{Count(d_i \,\&\, d_j \,\&\cdots\&\, d_k)} \tag{3}$$

C. Rule Refinement

One challenge of association rule mining is the threshold decision. Low level of support and confidence leads to overwhelming amount of rules. On the contrary, high thresholds may filter out useful rules. It is necessary to set the criterion for goodness evaluation. Jiao, Zhang, & Helander [19] proposed that a customer's affective satisfaction can be interpreted as the customer's expected utility embodied in a combination of affective descriptors, while his perceived utility is achieved via different configuration of design elements. Therefore, a goodness criterion is introduced as the difference between the expected and achieved utilities, shown in (4). The expected affective utility is represented as $U(\mathbf{d}_i)$ and observed affective utility as $U(\mathbf{e}_i)$. For each association rule, if the observed utilities are greater than the expected utilities, it is considered as good rule and retained. Otherwise it is regarded as poor rule and discarded.

$$\Delta U = U(\mathbf{e}_i) - U(\mathbf{d}_i) \tag{4}$$

where $$U(\mathbf{e}_i) = \sum_{k=1}^{m} \mathrm{u}_{ke} x_k + \varepsilon_i = \mathbf{X}\mathbf{u}_\mathbf{e} + \varepsilon_i \tag{5}$$

$$U(\mathbf{d}_i) = \sum_{k=1}^{n} \mathrm{u}_{kd} y_k + \varepsilon_i = \mathbf{X}\mathbf{u}_\mathbf{d} + \varepsilon_i \tag{6}$$

$\mathbf{d}_i$ stands for the vector of affective descriptors in the left side of the rule i, and $\mathbf{e}_i$ the vector of design elements in the right side of the rule i. To compare the utility from two different areas, (7) is introduced to normalize the expected and achieved utilities from (5) and (6).

$$u_{ij}^{*} = \left(u_{ij} - \min_{j \in \{1,2,\ldots,k\}} u_{ij} \right) / \sum_{i=1}^{m} R_i \tag{7}$$

D. Conjoint Analysis

Conjoint analysis is a well-established tool in marketing research for translating customer needs and expectation into product design elements [20]. It is based on a decompositional approach, in which subjects react to a set of total profile descriptions. It is the job of the analysis to find a set of part-worth utility for the individual attributes which are most consistent with the respondent's overall preferences, given some type of composition rule [21]. In this study, conjoint analysis is used to calculate customer expected utility $U(\mathbf{d}_i)$and achieved utility $U(\mathbf{e}_i)$.

V. CASE STUDY

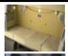
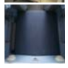
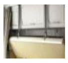
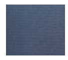
A. Elicitation of Affective Needs and Design Elements

A total number of 203 affective descriptors were collected from truck magazines and truck company websites. They were subject to industrial experts' examination. Among them, 61 adjectives were selected as the most relevant to truck cab design. 36 students from Nanyang Technological University were recruited to evaluate a range of truck cabs against each adjective. 7-point Likert scale was used ranging from 1(absolute not) to 3(not really) to 5(much) to 7(very much). Six Volvo truck cab pictures were shown to each subject. In total, 216 evaluations was collected, resulting in a 216×61 matrix. Clustering analysis was used to identify the affective dimensions of truck cab design. Ten clusters were retained to form the affective dimensions as shown in Table I. Meanwhile, the major design elements are identified by senior design engineers. A total of 18 design elements are recognized as shown in Table II.

TABLE I
AFFECTIVE DESCRIPTORS IN EACH CLUSTER

Code	Affective Descriptor
D1	Clean, Organized, Tidy
D2	Boring, Narrow
D3	Cool, Matched, Quiet, Silent, Calm
D4	Modern, Distinct, Ergonomic
D5	Luxurious, High-class, Long-lasting, Exciting, Safe, Secure, Soft, Deluxe, Fashionable, Bright
D6	Homey, Classy, Elaborate, Elegant, Good, Quality, Home-like
D7	Comfortable, Cozy, Durable, Nice, Peaceful, Practical, Relaxed, Stylish, Well-made
D8	Cheap, Dim, Dull, Normal, Obsolete, Simple, Ugly, Uncomfortable, Washable
D9	Functional, Fine, High-tech, Spacious, Warm
D10	Personal, Natural, Neat, Personalized, Private, Reliable, Special, Stain-resistant

TABLE II
TRUCK CAB AFFECTIVE DESIGN ELEMENTS

Code	Description	Figure	Code	Description	Figure
E1	Bunk—foldable		E10	Mats—textile	
E2	Bunk—unfoldable		E11	Mats—rubber	
E3	Storage—above bed		E12	Wall—sponge attached	
E4	Storage—beside bed		E13	Wall—flat	
E5	Seat material—fabric		E14	Interior color—yellow	
E6	Seat material—leather		E15	Interior color—green	
E7	Seat material—cloth with soft nap		E16	Interior color—blue	
E8	Light—embedded in the wall		E17	Interior color—red	
E9	Light—protruded from the wall		E18	Interior color—gray	

B. Description of Transition Data

The transaction database is part of the CATER project. Fifteen experienced truck drivers from Shanghai were interviewed to investigate their affective requirements of truck cab. The same 6 truck cab pictures were presented to the truck drivers. They were asked to evaluate each truck cab against the 10 affective dimensions. A sample response could be (d9, d7, e1, e3, e5, e8, e10, e13, e14), which means the truck cab is characterized as foldable bunk, above bed storage, fabric seat material, embedded reading light, textile mats, and yellow interior colour. The interviewee feels this configuration functional and comfortable. There were two missing data and thus 88 interview records were used.

C. Association Rule Mining

The 88 interview records were organized into transactional database. A data mining tool, Magnum Opus (Version 2.0), was employed to find the mapping relationships between affective needs and design elements. The setting of the searching criteria is shown in Fig.3. The mining process terminated with a set of rules containing 50 association rules, as shown in Table III.

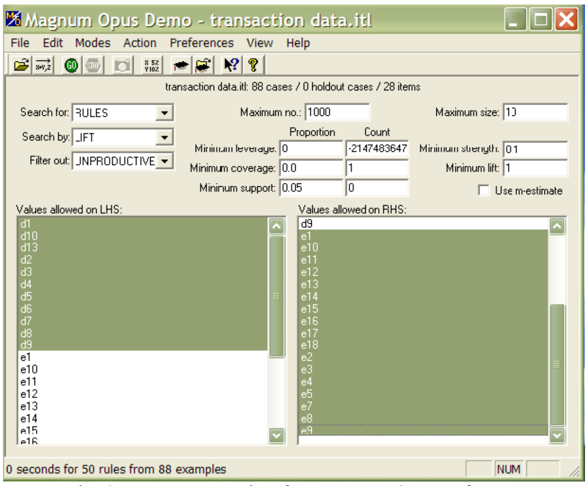


Fig. 2. Parameter setting for Magnum Opus software

TABLE III
IDENTIFIED ASSOCIATION RULES

Rule No	Association Rules	Support	Confidence	Lift
1	d9 ⇒ e14	0.114	0.556	3.26
2	d3 ⇒ e15	0.057	0.556	3.26
3	d3 ⇒ e11	0.057	0.556	3.26
…	…	…	…	…
47	d6 ⇒ e2	0.102	0.750	1.14
49	d9 ⇒ e3	0.148	0.722	1.10
50	d5 ⇒ e13	0.114	0.556	1.09

D. Conjoint Analysis

Conjoint analysis was applied for evaluating the part-worth utility of the design elements. Given all design elements as shown in Table II, a total number of $2 \times 2 \times 3 \times 2 \times 2 \times 2 \times 5 = 480$ possible product configurations. To overcome such an explosion of configurations by enumeration, orthogonal product profiles are generated based on the principle of Design of Optimal Experiment (DOE) [22]. Using Taguchi orthogonal array selector provided by SPSS software (www.spss.com), a total number of 27 orthogonal product profiles are generated. A separate group of 36 truck drivers was invited to act as the respondents for conjoint analysis. Each respondent was asked to evaluate all 27 profiles one by one and give the rank for all the profiles. This results in 36×27 groups of data. For each respondent, 27 regression equations are obtained by interpreting his original choice data as a binary instance of each part-worth utility. With these 27 equations, the part-worth utilities for this respondent are derived. Averaging the part-worth utility results in a segment-level utility for each design element. Table IV shows the part-worth utilities of each level of every design element. Simiarly, part-worth utilities of every affective descriptor were obtained as shown in Table V.

TABLE IV
PART-WORDTH UTILITY FOR EACH LEVEL OF DESIGN ELEMENTS

Design elements	level	Utility Estimate	Normalized utility
bunk	foldable	.079	.031
	unfoldable	-.079	0
storage	above bed	.287	.111
	beside bed	-.287	0
seat_material	fabric	-.093	.030
	leather	-.250	0
	cloth with soft nap	.343	.115
reading_light	embedded in the wall	.491	.190
	protruded from the wall	-.491	0
mats	textile	-.491	0
	rubber	.491	.190
wall	sponge attached	.211	.082
	flat	-.211	0
interior_color	yellow	.094	.167
	green	.192	.186
	blue	-.197	.111
	red	.678	.280
	grey	-.767	0

TABLE V
PART-WORDTH UTILITY FOR EACH LEVEL OF AFFECTIVE DESCRIPTORS

		Utility Estimate	Normalized utility
Clean	no	-.135	0
	yes	.135	.010
Boring	no	.253	.056
	yes	-.253	0
Quiet	no	-.076	0
	yes	.076	.187
distinct	no	-.250	0
	yes	.250	.018
luxurious	no	.024	0
	yes	-.024	.185
Homey	no	-.052	0
	yes	.052	.038
Comfortable	no	-.076	0
	yes	.076	.056
Cheap	no	.108	.080
	yes	-.108	0
Function	no	.372	0
	yes	-.372	.275
Personal	no	.007	.005
	yes	-.007	0

E. Rule Refinement

The proposed goodness evaluation criterion was used to refine the 50 rules in Table III. For each rule, difference between achieved utility and expected utility was calculated, indicated as U_O-U_E, in Table VI. An association rule is retained when U_O-U_E >= 0 and eliminated otherwise. In total, 19 rules were evaluated as good rules and formed the refined set of association rules.

TABLE VI
IDENTIFIED FULES FROM RULE REFINEMENT

Rule #	Rule	Observed utility	Expected utility	U_O-U_E
29	d8 ⇒ e17	0.28	0	0.28
17	d6 ⇒ e17	0.28	0.038	0.242
36	d7 ⇒ e8	0.19	0.056	0.134
42	d2 ⇒ e8	0.19	0.056	0.134
11	d7 ⇒ e14	0.167	0.056	0.111
22	d10 ⇒ e3	0.111	0.01	0.101
33	d5 ⇒ e17	0.28	0.185	0.095
18	d8 ⇒ e12	0.082	0	0.082
10	d6 ⇒ e7	0.115	0.038	0.077
26	d6 ⇒ e3	0.111	0.038	0.073
28	d2 ⇒ e3	0.111	0.056	0.055
32	d7 ⇒ e3	0.111	0.056	0.055
35	d6 ⇒ e12	0.082	0.038	0.044
47	d8 ⇒ e1	0.031	0	0.031
3	d3 ⇒ e11	0.19	0.187	0.003
40	d3 ⇒ e8	0.19	0.187	0.003
8	d8 ⇒ e18	0	0	0
9	d8 ⇒ e4	0	0	0
24	d8 ⇒ e9	0	0	0

VI. CONCLUSION

Affective product design implies a gradual shift of design focus from functional aspect to affective/emotional aspect. It evolves as an interdisciplinary research topic between human factors, industrial design and many other disciplines. In this paper, generic affective dimensions of truck cab design were structured. Association rule mining was used in this paper to reveal the mapping from customer affect to perceptual design elements. To refine association rules, a goodness criterion was introduced as the difference between customers expected utility and observed utility. A case study of Volvo truck cab design is presented based on the proposed methods.

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