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ROUGH SET BASED RULE MINING FOR AFFECTIVE DESIGN

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ABSTRACT
Affective design plays an important role in the development of products and services towards high value-added customer satisfaction. The main challenge for affective design is identified as how to translate affective customer needs into design elements. Towards this end, this paper formulates this problem as a rule mining process from the customer domain to the designer domain and proposes a rough set based *K*-optimal rule discovery method. A rule importance measure, taking rule semantics into account, is used to evaluate and refine the generated rules. A case study of truck cab interior design is also presented to illustrate the potential of the proposed method.

Keywords: Rule mining, affective design, rough set, K-optimal rule discovery

1 INTRODUCTION
Affective design aims at incorporating customers' affective needs into design elements that delivers customers' affective satisfaction [1]. Affect plays an important role in human information processing, such as perception, judgment [2], memory [3], and decision making [4], and so on. Hence, affect is a basis for the formation of human values and judgment. For this reason, it may be argued that product design models that do not consider affect are essentially inferior [5]. In addition, computer-aided product development technologies have reached a state of maturity so that design for performance or design for usability alone can no longer empower companies to sustain their competitive edges [6]. Traditional usability-based design approaches tend to facilitate product design in terms of customers' functional needs that are limited to physical and cognitive requirements [7]. Customers' affective responses to a product, however, so far have mainly been addressed from an advertising and marketing perspective only. This has lead to the dilemma that what customers expect from a product based on the way it is advertised always deviates from what it actually 'feels' like in a variety of aspects [8].
The main challenge for affective design is to grasp the customers' affective needs accurately and subsequently to translate affective needs into design elements (features) that match these needs [1]. It implies a mapping process from the customer domain to the designer domain, referred to as affective mapping. However, unlike approaches for structural articulation of functional requirements, such as requirement taxonomy [9], customer attribute hierarchy [10], and Functional Requirement (FR) topology [11], few structured forms about affective needs for affective mapping are known, due to a qualitative nature of affective needs and impreciseness and ambiguity in their linguistic origin. Although affective adjectives used in Kansei Engineering may alleviate the intangibility in describing affective needs to some extent [12], concrete mechanisms of affective mapping relationships seldom exist in practice [1]. In addition, customers tend to express their affective perception in a holistic fashion [13], whereas designers usually interpret affective needs as a collection of design elements (features), each of which contributes to certain affective aspects of the product. Coinciding with this mindset, affective quality is often evaluated according to a (weighted) sum of discrete assessments of each individual design element's contribution towards the achievement of the desired affective perception [14]. Such contextual mismatching impairs the ability to convey affective needs from customers to designers.
Usually affective customer needs are identified as a set of affective descriptors. A large amount of affective adjectives are collected concerning the consumers' feelings toward a product through user interviews, focus groups or surveys [12]. Then, the most relevant and appropriate terms are selected by domain experts, ranging in numbers from several dozens to several hundreds. The selected ones are further scrutinized and structured, either manually or statistically. In essence, there are two types of

mapping: qualitative and quantitative mapping. As for qualitative mapping, the simplest way is manual mapping, such as the Category Identification method [12]. Focus groups are used to provide reality checks on the usefulness of a new product design [15]. Quantitative methods include mainly statistical methods such as multivariate analysis. In addition, it is common to use regression analysis to compare customer characteristics and to determine their overall rankings. Some tools for this task are readily available, including multiple linear regression analysis [16] and general linear models [17]. Most affective descriptors, such as 'beautiful or not', do not exhibit linear characteristics. As a matter of fact, affective responses to products are fuzzy and vague in nature, thus assuming nonlinear characteristics [18]. As such, more advanced methods, including quantification theory type I, II, III, and IV [18], neural networks, genetic algorithms, and fuzzy logic [19], are deemed to be appropriate. Ishihara et al. [20] apply neural network techniques to enhance the inference from Kansei words (affective adjectives) to design elements. Arakawa et al. [21] emphasize the properties of fitness functions for optimization of Kansei using genetic algorithms. Tsuchiya et al. [22] propose a procedure combining genetic algorithms and fuzzy logic for identifying affective needs regarding driving comfortableness of automobiles.

In order to explicitly identify relationships between the customer domain and the design domain, this paper proposes to apply data mining techniques to improve the identification of customers' affective needs and the mapping of these needs to affective design elements, by reusing historical product and sales data. Data mining is a process of discovering previously unknown, potentially useful and understandable patterns from large data sets [23]. Jiao et al. [1] apply data mining techniques to identify affective mapping patterns as association rules. Despite the fact that a large number of association rules can be generated in the first place, semantics and logics regarding these rules must be further scrutinized and refined before any useful knowledge pattern can be deployed for decision making. Towards this end, this paper applies the *K*-optimal rule discovery method [24], owing to its strength in dealing with semantics in the rule mining process [25].

Further, the assessment of affectability of a given product has been traditionally carried out by experts, based on both their experience and rules of thumb. Assessment of affective satisfaction has been historically done on an ad hoc basis [26], where a number of heuristics are assumed a priori. In order to systematically evaluate affective satisfaction on a scientific basis, it is imperative to develop objective measures for the subjectivity and vagueness of affective needs. To address this problem, an importance rule measure based on the rough set theory is used, owning to its analytical power in dealing with rough, uncertain and ambiguous data [18, 27].

2 RULE MINING FORMULATION

In this paper, affective mapping is formulated as a rule mining process from affective needs in the customer domain to design elements in the designer domain. Affective needs are usually expressed as a set of affective descriptors $D = \{d_i\}_I$, where I denotes the total number of affective needs in terms of affective descriptors. Target customers constitute a set, $C = \{c_t\}_T$, where T is the total number of customers. The affective needs of the *i*-th customer, $c_i \in C \mid \exists i \in \{1,...,T\}$, can be expressed as a subset, $D_i = \{d_i\}_{T_i}, D_i \subseteq D$, where T_i is the total number of this customer's affective needs.

Meanwhile, various product design elements can be extracted from the product documentation. These elements can be characterized by another set, $E = \{e_i\}_M$, where M is the total number of design elements. Each design element, $\forall e_i (1 \le i \le M)$, may assume a number of element levels, $E_i^* = \{e_{ik}^*\}_{L_k}, 1 \le k \le L_k$, where L_k is the total number of levels (instances) of e_i, and k denotes the *k*-th level of e_i. For example, the interior color (i.e., a design element) of a truck cab can have five element levels (blue, red, yellow, red, and grey, see Table 1).

A possible combination of design elements with appropriate levels can be configured into a desired product specification, P_q ($1 \le q \le Q$, Q is the total number of products) with regard to affective needs of the customer c_i. This combination can be expressed as a set, $P_q = \{e_{12}^*, e_{21}^*, ..., e_{J4}^*\}$, where $J \le M$ is the total number of design elements in this specification. This means that product P_q is a combination of the first, second and *J*-th design elements with the second, first and fourth element levels, respectively.

Customer affective responses are usually associated with a holistic impression of the product, rather than summation of affective quality from individual design elements. However, customers may select a design element with a specific desired element level. The mapping relationships from affective needs (D_i) to a particular product specification (P_q) are denoted as mined rules $D_i \Rightarrow P_q$, where an individual rule $d_i \Rightarrow e_{ik}^*$ indicates an inference from the antecedent ($d_i \in D_i$) to the consequent ($e_{ik}^* \in E_i^*$).

3 ROUGH SET BASED K-OPTIMAL RULE DISCOVERY

This paper examines the rule mining problem using *K*-optimal rule discovery, which is a well-established data mining technique that returns the *K* most interesting rules according to specified measures [24, 25]. It can also speed up the rule discovery task by allowing pruning of areas of the search space that is devoid of the top *K* most valuable rules. In the context of rule mining, a general rule can be formulated as $d_i \,\&\, d_j \,\&\cdots\&\, d_k \Rightarrow e_{ia}^* \,\&\, e_{jb}^* \,\&\cdots\&\, e_{kc}^*$, where $d_i, d_j, d_k \in D_i$, $1 \le i < j < k \le I$ and $e_{ia}^* \in E_i^*, 1 \le a \le L_a, e_{jb}^* \in E_j^*, 1 \le b \le L_b, e_{kc}^* \in E_k^*, 1 \le c \le L_c, 1 \le i < j < k \le M$. The rule can be interpreted as the occurrence of affective descriptors $\left(d_i,...,d_j,...,d_k\right)$ associated with the occurrence of design elements e_i with *a*-th level, e_j with *b*-th level and ,…, e_k with *c*-th level. It can be concisely denoted as $X^d \Rightarrow Y^e$, where item set $X^d = \left\{d_i,\ d_j\ ,\ldots,d_k\right\}$ and item set $Y^e = \left\{e_{ia}^*, e_{jb}^*,..., e_{kc}^*\right\}$ are nonempty sets of conditions called the antecedent and consequent, respectively.

K-optimal rule discovery can be expressed as a 5-tuple $\langle C,\Delta,G,\lambda,K\rangle$, where C is a nonempty set of conditions; Δ is a database of records $R = \left\{R_h\right\}_H, R \subseteq C$, where H is the total number of the records, $R_h = P_h \cup D_h$ is the *h*-th record, and $D_h = \left\{d_i^h,\ d_j^h,\ldots,d_k^h\right\}$, implying product P_h configured by certain design elements is associated with affective needs D_h; G is a set of constraints on the rules in the solution space; $\lambda:\left\{X^d \Rightarrow Y^e\right\}\times\Delta\to\mathbb{R}$ is a function from rules and databases to real values and defines a value measure such that the greater $\lambda\left(X^d \Rightarrow Y^e,\ \Delta\right)$, the greater the (potential) value to the user of the rule given the database; and K is the number of rules to be discovered. The procedure is as follows: First, the user specifies the rule value measure λ, a set of constraints G and the number of rules to be discovered K. The system then returns the K rules that optimize λ with respect to the database Δ within constraints G. The solution $\left\{\langle C,\Delta,G,\lambda,K\rangle\right\}\to\left\{X^d \Rightarrow Y^e\right\}$ is a function, satisfying the following:

$$
\begin{aligned}
&\forall s \in \text{solution}\left(\langle C,\Delta,G,\lambda,K\rangle\right): \\
&\quad \left(s \subseteq \text{CSsolution}\left(\langle C,\Delta,G\rangle\right)\right) \wedge \left(|s| \le K\right) \wedge \\
&\quad \left(\neg\exists r \in \text{solution}\left(\langle C,\Delta,G,\lambda,K\rangle\right):\ |r| < |s|\right) \wedge \\
&\quad \left(\neg\exists X \Rightarrow Y \in s, U^d \Rightarrow V^e \in \left(\text{CSsolution}\left(\langle C,\Delta,G\rangle\right) - s\right): \lambda\left(X^d \Rightarrow Y^e,\Delta\right) < \lambda\left(U^d \Rightarrow V^e,\Delta\right)\right),
\end{aligned} \tag{1}
$$

where CSsolution denotes a function to obtain solutions to a constraint-satisfaction rule discovery task (Webb and Zhang, 2005), and

$$
\text{CSsolution}\left(\langle C,\Delta,G\rangle\right) = \left\{X^d \Rightarrow Y^e \middle| \left(X^d \subseteq C\right) \wedge \left(Y^e \subseteq C\right) \wedge \left(\text{satisfies}\left(X^d \Rightarrow Y^e,\Delta,G\right)\right)\right\}. \tag{2}
$$

K-optimal rule discovery uses *leverage* as the value measure λ, and with respect to the rule $X^d \Rightarrow Y^e$, it is defined as follows (Webb, 2003):

$$
\text{leverage}\left(X^d \Rightarrow Y^e\right) = \text{support}\left(X^d \cup Y^e\right) - \text{support}\left(X^d\right) \times \text{support}\left(Y^e\right), \tag{3}
$$

where $\text{support}(\bullet)$ is the proportion of records that contain item set '•', For example the support of item set X^d is defined as follows:

$$\text{support}\left(X^d\right)=\left|\left\{X \mid \left(X \in \Delta\right) \wedge \left(X \supseteq X^d\right)\right\}\right| / H, \tag{4}$$

where X is an item set in the database Δ and $|\bullet|$ denotes the cardinality of a set. Leverage is the difference between the observed frequency of $X^d \cup Y^e$ and the frequency that would be expected if X^d and Y^e are independent. In other words, it measures the number of additional records that an interaction between X^d and Y^e involves above and beyond those expected if one assumes independence of X^d and Y^e. This directly represents the volume of an effect and hence will often directly relate to the ultimate measure of interests to the user such as the magnitude of the profit associated with the interaction between X^d and Y^e.

K-optimal rule discovery generates *K* valuable rules and employs leverage to quantitatively measure the "quality" of the rules. However, the real value of a rule, in terms of usefulness and importance, is subjective and depends heavily on the particular domain and business objectives. Usually, in order to find enough rules, the value of *K* is large. Hence, it is often a tedious task for domain experts to evaluate rules manually. Therefore, it is necessary to specify criteria for rule goodness evaluation. Before the target data is fed into the system for *K*-optimal rule discovery, redundant attributes can be excluded by a rough set approach [28], based on which rule generation would be more efficient and more effective [27].

One important concept in rough set theory is reduction. A reduct is defined as a subset of attributes in a decision table that by themselves can fully characterize the knowledge in that decision table [28]. Based on Li and Cercone [27], let $\{\Pi_r\}_R$ and $\{\Phi_r\}_R$ be the respective sets of reducts and rule sets, where R denotes the total number of both reducts and rule sets, as each rule set Ω_r is generated from reduct Π_r. Assume $\phi_i \in \Phi_r (i=1,...,R_r)$ is an individual rule from rule set Φ_r, where R_r is the total number of rules in the Φ_r. Then the rule importance measure ρ_i for the individual rule ϕ_i is the total number of this rule generated in all the possible rule sets divided by the number of reducts, as shown in Formula (5). For example, if there are 10 reducts and ϕ_i appears in 6 out of 10 rule sets, then ρ_i is 60%.

$$\rho_i = \frac{\left|\left\{\Phi_r \in \Omega \middle| \phi_i \in \Phi_r\right\}\right|}{R}, \tag{5}$$

where $|\bullet|$ denotes the cardinality of a set. The rule importance measure is objective which provides a straightforward and direct view for evaluation purposes and capitalizes on the concepts of reducts to removes redundant attributes [27].

4 CASE STUDY

4.1 Affective Need Elicitation

A case study of the interior design of a truck cab is presented to demonstrate the affective mapping approach proposed. As shown in Figure 1, a total of seven design elements are identified from six existing truck cabs by senior design engineers, taking into account factors such as cost, material, style, and manufacturability. These design elements are further categorized into 18 levels of instances, as shown in Table 1. A total number of 203 affective descriptors are identified from truck magazines and truck company websites. After consultation with industrial experts and human factors specialists, a total of 61 adjectives are selected as the ones most relevant to describe affective aspects of a truck cab. These affective adjectives comprise the semantic space of affect for truck cabs.

Figure 1. Truck cab interior design

Table 1. Design elements and their levels for truck cabs

Code	Description	Code	Description	Code	Description
e_{11}	Bunk-foldable	e_{33}	Seat material-cloth with soft nap	e_{62}	Wall-flat
e_{12}	Bunk-unfoldable	e_{41}	Light-embedded in the wall	e_{71}	Interior color-yellow
e_{21}	Storage-above bed	e_{42}	Light-protruded from the wall	e_{72}	Interior color-green
e_{22}	Storage-beside bed	e_{51}	Mats-textile	e_{73}	Interior color-blue
e_{31}	Seat material-fabric	e_{52}	Mats-rubber	e_{74}	Interior color-red
e_{32}	Seat material-leather	e_{61}	Wall-sponge attached	e_{75}	Interior color-gray

4.2 Affective Descriptor Analysis

Affective descriptor analysis is used to extract typical affective descriptors from the affective semantic space formed by the 61 affective adjectives identified. As affective needs are generally vague and highly unstructured, analytical tools with large tolerance for ambiguity and high level of prediction accuracy are needed to conduct the affective descriptor analysis. Among many others, clustering analysis, as the black box prediction engine, can be very effective and is often among the best performers when applied to real data problems (Friedman et al., 2001).

Differential Emotions Scale (DES) analysis (Osgood et al., 1975) is first used with 7-point Likert scale, ranging from 1 (absolutely not) to 3 (not really) to 5 (much) to 7 (very much) by 36 participants. In total, 216 evaluations for six existing truck cabs are collected, producing a 216×61 matrix. This data is then subject to clustering analysis, aiming to group similar adjectives together. Hierarchical clustering analysis with a complete linkage agglomerative method (Friedman et al., 2001) is used to find representative affective descriptors. A dendrogram with 30 nodes is generated and depicted in Figure 2. It consists of many inverted U-shaped lines connecting nodes in a hierarchical tree. The height of each inverted-U represents the distance between the two nodes being connected, which provides a complete description of the hierarchical clustering in a graphical form. Cutting the dendrogram horizontally at a particular height partitions the data into disjoint clusters represented by the vertical lines that intersect it. A reasonable level of granularity is to group the affective adjectives into 10 clusters cut by the horizontal line shown in the figure. The representative affective descriptor for each cluster is shown in Table 2.

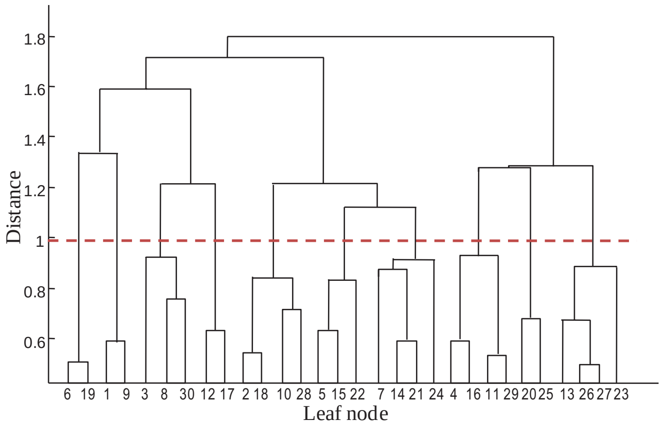

Figure 2 Dendrogram of affective descriptor clustering analysis

Table 2 Clustered affective descriptors for truck cabs

Descriptor	Code	Descriptor	Code
Clean	d_1	Homey	d_6
Boring	d_2	Comfortable	d_7
Cool	d_3	Cheap	d_8
Modern	d_4	Functional	d_9
Luxurious	d_5	Personal	d_{10}

4.3 Affective Rule Mining

The transaction database is obtained from fifteen experienced truck drivers via an interview (http://www.cater-ist.org/), where each driver is asked to evaluate six truck cabs against 10 affective descriptors. Each record in the database denotes the presence of a set of affective needs and the corresponding customers' selection of design elements. A sample record (see No. 3 in Table 3) is (e_{11}, e_{21}, e_{31}, e_{41}, e_{51}, e_{62}, e_{71}, d_5, d_9), which indicates that the truck cab is characterized as follows: '*foldable bunk, above-bed storage, fabric seat, embedded light, textile mats, flat wall, and yellow interior*'; the associated affective needs are '*functional and luxurious*'. Two records are missing and thus 88 records are organized into the transaction database. A selected part of these records is shown in Table 3.

Table 3 Transaction database

No.	bunk	storage	seat_material	light	mats	wall	interior_color	affective descriptor
1	e_{12}	e_{21}	e_{31}	e_{41}	e_{51}	e_{62}	e_{71}	d_7&d_9
2	e_{12}	e_{21}	e_{31}	e_{41}	e_{52}	e_{62}	e_{72}	d_3
3	e_{11}	e_{21}	e_{31}	e_{41}	e_{51}	e_{62}	e_{71}	d_5&d_9
…	…	…	…	…	…	…	…	…
86	e_{12}	e_{22}	e_{31}	e_{41}	e_{51}	e_{62}	e_{73}	d_2
87	e_{12}	e_{21}	e_{31}	e_{41}	e_{51}	e_{61}	e_{74}	d_8&d_{10}
88	e_{12}	e_{21}	e_{33}	e_{42}	e_{52}	e_{62}	e_{74}	d_6&d_{10}

A Rough Set Exploration System (RSES) [29] is used to generate reducts with genetic algorithms as shown in Table 4. A *K*-optimal rule discovery algorithm is then employed to generate rule sets for each reduct set with the data mining tool – MagnumOpus [25]. In this example, the value of *K* for each reduct is 20. The set of constraints *G* is restricted by setting the minimum support at 0.04, minimum confidence at 0.2 , maximum size of the antecedent of a rule at 4, and a single condition (i.e., only one affective descriptor) in the consequent only.

Table 4. Reducts generated by RSES with genetic algorithms

No.	Reducts
1	{bunk,storage, mats, wall}
2	{bunk, mats, interior color}
3	{bunk, seat_material, interior_color}
4	{bunk, lights, interior_color}

4.4 Result and Analysis

The results are ranked by the rule importance measure (larger than 25%) as shown in Table 5. The leverage, support, and confidence of each rule are also given.

Table 5. FAM relations ranked by the rule importance measure

No.	Rules	Rule Importance measure	Leverage	Support	Confidence
1	$d_9 \Rightarrow e_{11}$	100%	0.050	0.068	0.333
2	$d_8 \Rightarrow e_{12}$	100%	0.015	0.273	0.960
3	$d_9 \Rightarrow e_{71}$	75%	0.079	0.114	0.556
…	…	…	…	…	…
20	$d_6 \Rightarrow e_{42}$	50%	0.027	0.045	0.222
21	$d_2 \Rightarrow e_{74}$	50%	0.025	0.068	0.500

The *K*-optimal rule discovery method returns a controllable number of rules that optimize the rule value measure λ (leverage) within the constraints G. In this case study, there are 196 rules generated from the original data with the only constraint on support (0.04) and confidence (0.2) whereas the numbers of rules are reduced to 29, 34, 24, and 24 for each reduct with the same constraints. In addition, the *K*-optimal rule discovery algorithm further reduces the rule number to 20 for each reduct (i.e., K = 20, depending on different situations). Rules 1 and 2 (if the bunk is foldable, then it is functional; if the bunk is unfoldable, then it is cheap) have an importance of 100%, which are said to be more important than other rules. While support is usually used to measure how frequently the items appear together, it cannot provide the significance of a rule. The leverage measure addresses the rules in terms of the independence between the antecedent and consequent. In other words, it takes a perspective of the degree of interaction between affective needs in the customer domain and design elements in the designer domain. On the other hand, these mined rules are used to predict the relationships between two domains for future affective design. So accuracy and generality are two critical measures. Accuracy is often based on cross-validation while generality is for future data. Leverage is also called 'weighted relative accuracy' which trades off generality and relative accuracy [30]. Further, the rule importance measure takes the semantic meaning of the data into consideration, and evaluates the significance of a rule based on the significance of attributes [31]. This is very important to leverage the 'ambiguous' affective customer needs, as it often entails additional effort to interpret the outcome and to judge the validity of the outcome by domain experts.

Another point worth pointing out is that people's affective perception of products is not just the sum or weighted sum of its design elements, but more precisely the patterns in the way people and products interact in a holistic fashion [13]. In this sense, it is arguable that one very negative single element can destroy the positive emotions towards the whole product. Although the rules generated in the form of single element associated with one or more affective descriptors, these inferred rules are derived based on previous interactions between customers and products in a holistic fashion. One particular rule can be traced back to the previous interaction scenario such that the designer is aware of other design elements in that product. Nevertheless, if designs resulted from the rules-of-thumb by individual designers will not have this valuable information. In addition, not only positive affective descriptors are encoded, but also negative ones (e.g., boring). Those elements associated with negative ones can be identified such that it can avoid the situations when one negative single element can destroy the overall positive emotions.

5 CONCLUSIONS

The purpose of affective mapping is to find valuable relationships between the customer domain and the designer domain for future design. Rough set based *K*-optimal rule discovery effectively mines valuable rules, with consideration of interactions between customers and designers using leverage as the measure. Further these rules are ranked by the rule importance measure by taking rule semantics into account. Therefore, the mined rules can act as an interface between customers and designers. While the customer domain depicts how customers perceive and respond to products holistically in terms of their affective appealing, the design domain delineates how the designer can achieve affective design by configuring available design elements based on the acquired rules. As a result, given a particular customer's affective needs, the designer can configure the product in a personalized way without the tedious elaboration process with the customer and marketing staff. In such a manner, companies, in pursuit of products that are not only safe and efficient, but also pleasurable to use in terms of customers' affective satisfaction are more likely to gain competitive edges.

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