

Identification of Customers' Latent Kansei Needs and Product Design By Rough Set Based Approach

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Abstract

Purpose – This paper proposes a new rough set based kansei engineering methodology, in which rough set model analyzes the interaction effects between principal components presenting customers' need element and between product design category elements, and discusses its effectiveness and limitation through an application example to kansei product development.

Methodology/approach – Rough set model is a promising method to analyze the interaction effects, important information for kansei product design which traditional statistical analysis was difficult to find out. We applied the proposed methodology to kansei product development project of car floor carpet for new car design and compared it with traditional kansei engineering methodology. Based on the proposed methodology, we clarified the patterns of customers' needs to car floor carpet and identified design element pattern rules to realize customers' needs.

Findings – Rough set based approach was very useful in that it is able to clarify customers' latent needs as a combination of principal component elements and relates them to product specification considering its significant interaction effects. Rough set model could clarify customers' latent needs, and then find new design elements interacting the design elements, which were not found out by traditional statistical analysis. At the present research stage, this paper suggests that it is beneficial for product designer/engineer to use rough set model, statistical analysis and his/her expert knowledge.

Research limitation/implication – Rough set based approach to kansei engineering provides more information on customers' needs about product and product design specification. Moreover, it enables a consistent analysis from the identification of customers' needs to design specifications fitted to customers needs. The proposed methodology provides a useful procedure for product designer/engineer to develop "customer-oriented product".

Originality/value – This paper challenges traditional kansei engineering methodology and offers a new rough set based methodology for kansei engineering. It was shown that the proposed methodology was more useful in the practical kansei product design than the existing methodology, especially in the identification of customers' latent needs and the clarification of interaction effects between design

elements.

Keyword – Customers' needs, kansei product design, rough set based kansei engineering methodology.

Paper type – Research paper.

1. Introduction

This paper proposes a rough set based methodology for kansei engineering, which identifies customers' latent needs represented by the combination of principal components and transforms them to product design elements. The methodology includes the rough set model proposed by the authors (Nishino, 2005a; Nishino, Nagamachi, and Tanaka, 2005b; Nishino, Nagamachi and Tanaka, 2006a). The authors have developed a probabilistic rough set model to analyze kansei evaluation data effectively, and have examined its effectiveness to some product design applications (Nishino, Nagamachi and Sakawa, 2006b; Nishino, Nagamachi, Sakawa, Kato and Tanaka, 2006c). On the basis of the developed rough set model, this paper proposes a rough set approach to kansei engineering methodology. An advantage of the methodology is to provide a method to a systematic approach to the process analysis from the clarification of customers' needs analysis to the identification of design elements or element set. More essential advantage is that it takes account for interactions among elements; interactions among customer elemental needs, interactions among design elements. Human perceives the interactions or "Gestalt" as well as each element of object, and then recognizes or feels it. In kansei engineering (KE) methodology, there were no methods explicitly to model the interactive effects between related elements so far. Rough set based kansei engineering approach is promising in that point because it is good to catch interactions among elements (Nishino and Nagamachi, 2007). By using the proposed rough set based kansei engineering methodology, you will be able to obtain more significant information on kansei product design configuration including the interactive relations between customer elemental needs and between product design attributes.

In this paper, we will propose a rough set based methodology for kansei engineering, and introduce an application example of the methodology to new car floor carpet development project to show its effectiveness. Second section of the paper will describe proposed methodology in which its steps will be described, but the mathematical detail of rough set model will be omitted. Third section will show the results of an application example of the methodology to new car floor carpet development for new car design. In final section, we will conclude the paper and describe future works.

2. Rough set based methodology

2.1 Features and advantages of rough set based methodology

This section describes the main features and advantages of proposed kansei engineering methodology, and then outlines its steps. It was based on the strategic multilevel decision rule extraction model by using rough set model (Nishino and Nagamachi, 2007). The methodology aims to link customers' latent needs, development concepts, and design attributes.

The first important features is that it searches the combination between principal component elements in order to see more deeper customers' latent needs using rough set

model. From customers' latent needs, one can see long-range needs for product development. Traditional kansei engineering approach as well as modern marketing research is not successful to identify long-range customers' needs. The identification of customers' needs is very of importance in kansei engineering methodologies because kansei engineering methodologies should be more directed to customer-oriented development.

The second feature is to discriminate kansei words and decision words. Kansei words are feeling to product such as "beautiful", "higher quality feeling" and so on. On the other hand, decision words are decisive words such as "attractive", "want to buy" and "want to use" which are directly related to customer purchase behavior. We assume that customers discriminate kansei words and cognitive decisive words. In product development from kansei viewpoints, it is essential to see kansei words linked to customer purchase.

The third feature is to identify the combination of design elements as well as each design element contributing to kansei words. Human perceps the interactions or "Gestalt" as well as each element of object, and then recognizes or feels it. It has been much difficult to extract the interactions of design elements contributing to kansei words. Rough set approach adds these features to traditional kansei engineering methodology.

2.2 The steps of methodology

Figure 1 shows a flow of proposed kansei engineering methodology. Left hand side shows the identification steps of customer needs and design elements satisfied with customers' needs. The analytical methods necessary to each step is shown at right hand side.

First step is concept gathering in which we should collect information including developing concepts, image key words and social evaluation words of product.

Step 2 is the deployment of information obtained at step 1 to kansei words. Mainly, product planners or designers perform the step. The key point at this step is faithful deployment from product image and developing sentence. On the other hand, we should select decision words related to direct purchase of customers such as "attractive", "want to buy" and "want to use".

Step 3 is to identify the customers' elemental need to the product by using principal component analysis or factor analysis often used in traditional kansei engineering methodology. From the result, we can know customers' elemental need as a principal component.

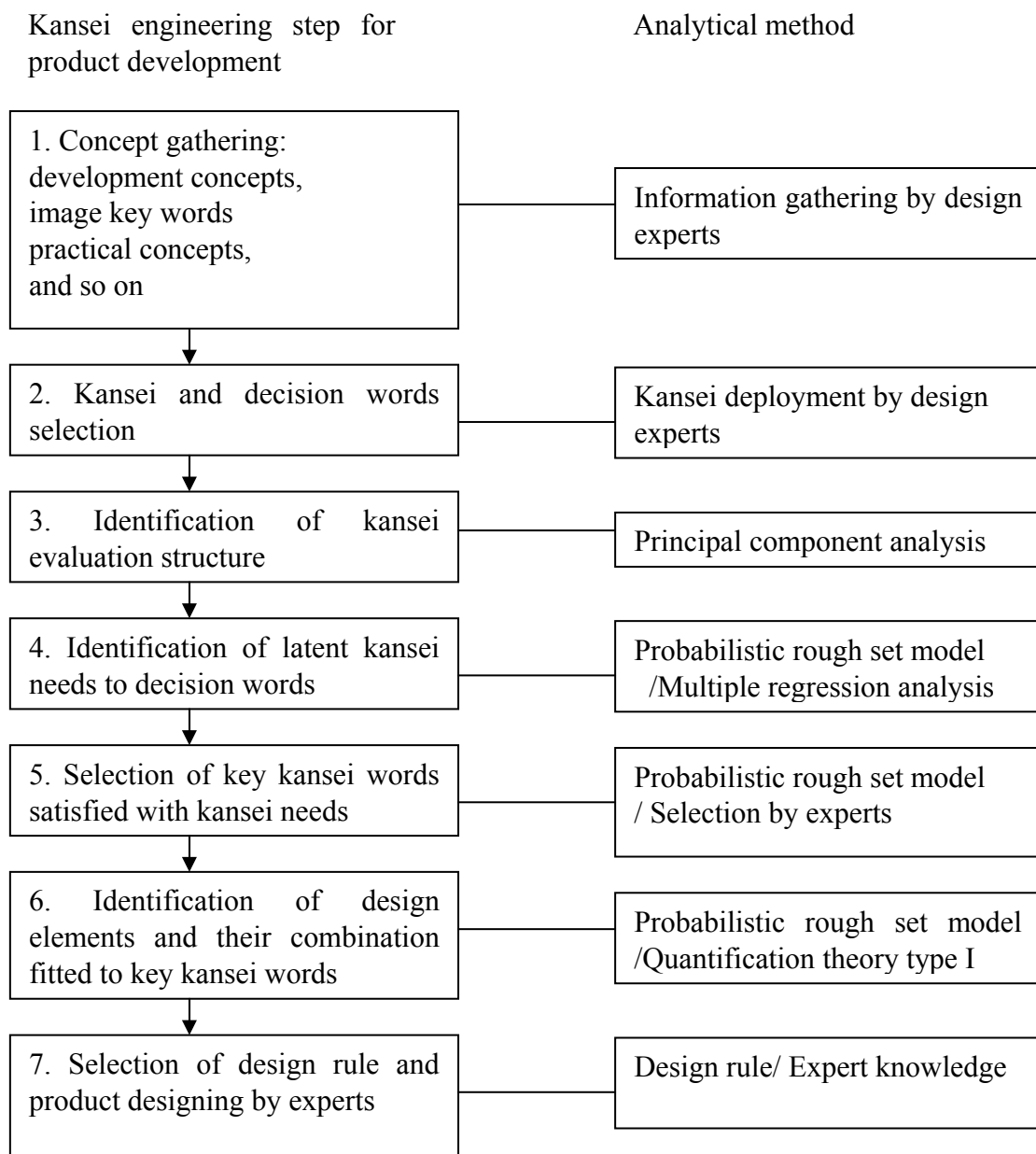
Step 4 is to know how customers' latent need as combination of elemental need affects decision words such as "want to buy", "attractive" and so on. We assume that customers' latent needs are represented as combination of elemental needs. The acquired information must be more useful to know a long-range trend of customer wants for product development. At the step, multiple regression analysis /rough set analysis is useful tool. Especially, rough set analysis is useful to know deeper customers' latent needs because it can clarify them as the effect of combination between customers' elemental needs.

Step 5 is to select kansei words satisfied with the customers' latent needs. There are two methods; rough set analysis and expert selection method. The former analyzes the

relation between the principal component combination and kansei word combination, and then identifies the key kansei words to customers' needs (Nishino and Nagamachi, 2007). The latter is that experts are to select key kansei words referring to the results of principal component analysis.

Step 6 is to identify the design elements and their combination fitted to the selected key kansei words. At this step, one can use quantification theory type I (QTI) /rough set analysis. In the case that there are severe interaction effects between design elements, rough set analysis as well as QT I should be used. Moreover, one can extract different decision rule set by alternating rule evaluation measures; general rule set and specific rule set.

Step 7 is the selection of obtained design rules in view points of useful design rules by experts, and the product design based on the decision rules and expert knowledge. Domain experts had better select "good rules" among the extracted ones by rough set analysis because mathematically extracted decision rules are often technically impossible or uninteresting for design experts.



3. Application example to kansei design of car floor carpet

3.1 Experimental conditions

Samples are 25 samples of car floor carpet collected from different Japanese automobile company as shown in Figure 1. Kansei words were 21 kansei words extracted from image key words, new developing car concept and the present car concept of company and practical evaluation concepts such as “good sense”, “good shape”, “fashionable”, “sporty”, “clean” and so on. Four decision words were selected as decision words directly related to customer purchase such “attractive”, “want to use”, “like” and “want to buy”.

Subjects are 43 male and 8 female employees, aged 20s to 60s. Each subject evaluated



Figure 2. Experimental samples

all the samples while they see and touch them. Each word was measured by 5-point semantic differential (SD) scale.

3.2 Principal component analysis

We computed principal components from the evaluation data of 21 kansei words except decision words. Three significant components were obtained as shown in Figure 2. We can interpret a principal component as a customers' elemental need and customers' latent needs are combinations of elemental needs. Regrettably, because the first component "Factor X- Not factor X " was a key concept in the designing new carpet for new car development and it is secret, we cannot show its concrete concepts here. "High quality-Not high quality" component includes "higher quality feeling", "good shape", "good sense" and so on. "Clean – Unclean" component includes "clean" and so on.

Table I. Principal component

Principal component	Eigen value	Contribution(%)	Accumulated contribution(%)
Factor X - Not factor X	1.60	65.86	65.86
High quality -Not high quality	0.48	19.73	85.59
Clean - Unclean	0.18	7.39	92.99

3.3 Combinations of elemental kansei needs

Table II shows extracted main decision rules for each decision word in order of coverage measure. Certainty indicates the degree for a rule to predict decision word. Coverage indicates the range of customers covered by the rule. Effect measure indicates the realistic effect of a rule normalized by the occurrence frequency of plus or minus score in samples. In decision rule column, A1 is Factor X, A2 is Not factor X, B1 is High quality, B2 is Not high quality, C1 is Clean, and C2 is Unclean, For example, there are two significant rules for decision word "Like"; B1A1 (High quality and Factor X), C2A1 (Unclean and Factor X). The rule B1A1 has higher certainty and coverage than C2A1. We assume that the combination of principal components represents customer' latent kansei needs. No single element rule was not obtained. This suggests that customers' latent needs have some clusters and make the combination of some principal components. The rule A1 B1C1 for the decision word "fit to new car" may be good for product development because of its higher measures. However, the rule may be selected from strategic viewpoints of product development.

To compare with rough set results, Figure 3 shows the ratio of standard regression coefficient of each component for "want to use" and " fit to new car". For example, it should be noticed that the ratio of "fit to new car" is similar to rough set result. For "want to use", while regression analysis suggests higher quality (B1), rough set suggests the combination of not higher quality (B2) and factor X (A1) or clean (C1). However, regression analysis has no rational reasons to construct the combination of principal components because it is statistical linear model of principal components. On the other hand, rough set model explicitly deals with the combination of principal components.

3.4 Selection of key kansei words satisfied with customers' latent needs

In the case, product design experts selected some kansei words from principal components related to customers' needs, such as "word X", "higher quality feeling" and so on. Regrettably, we cannot show kansei "word X" here, because the word is very

Table II. Combination of components rough set

Decision word	Decision rule	Support	Certainty	Effects	Coverage
Like	B1A1	105	0.294	1.609	0.451
	C2A1	51	0.250	1.368	0.219
Want to use	A1B2	58	0.227	1.142	0.228
	C1B2	34	0.222	1.115	0.134
Attractive	A1C2	51	0.250	1.255	0.201
	C2A1	55	0.270	1.469	0.235
Want to buy	A1B2	53	0.208	1.238	0.248
	C1B2	30	0.196	1.168	0.140
	A1C2	48	0.235	1.402	0.224
Fit to new car	A1B1C1	93	0.365	1.735	0.347

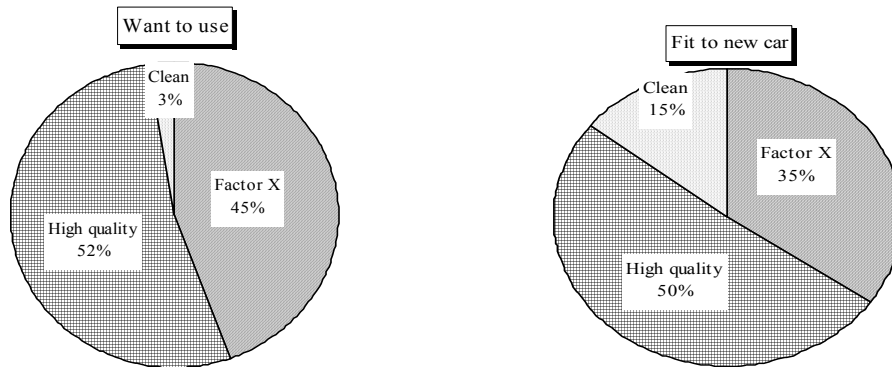


Figure 3. Ratio of standard regression coefficient

important one for newly developing product and it is secret.

3.5 Identification of design elements fitted to key kansei words

3.5.1 Analysis by quantification theory type I (QT I)

Table III shows the results of "higher quality feeling" by QT I. Total number of items and categories were 33 and 199 respectively. Some items were grouped as an analysis unit according to technologically related items. For example, a basic design unit includes "basic color", "brightness", "surface color", "material" and so on as shown in the top of Table III. A pile design unit includes "pile type", "pile color pattern", "pile pattern" and "basic pattern" as shown in the bottom of Table III.

We constructed six units considering interactions among items. We have executed QT I using a unit. We obtained good regression equations for predicting kansei words as indicated by a multiple regression coefficient.

You can see that the design elements for "higher quality feeling" in the basic design analysis unit are "middle brightness in color" or "1350-2000 in length" by checking partial regression coefficients and category scores. In pile analysis unit, the design elements for "higher quality feeling" are "cut in pile type" and "diagonal in pile pattern".

In this way, one can obtain important information on design elements for designing kansei product by QT I. Moreover, we also obtained good information for the other key kansei word.

Table III. “Higher quality feeling” by QT I

Item	Category	Category score	Correlation	Partial correlation	Multiple correlation
Basic color	1 black	0.069	-0.025	0.508	0.869
	2 brown	-0.177			
Brightness	1 high	0.231	0.396	0.777	
	2 middle	0.350			
	3 low	-0.299			
Surface color	1 one	0.048	0.084	0.375	
	2 two	0.012			
	3 three	0.068			
	4 over four	-0.221			
Material	1 nylon	0.008	0.105	0.014	
	2 PP	-0.001			
Surface hair	1 intermingle	0.121	0.347	0.747	
	2 middle strong twist	0.136			
	3 strong twist	-0.363			
	4 others	0.056			
Length	1 1350~2000	0.238	0.352	0.679	
	2 2001~2500	0.006			
	3 2501~3000	-0.036			
	4 over 3001	-0.320			
Touch	1 hard	0.009	-0.054	0.494	
	2 a little hard	-0.235			
	3 a little soft	-0.153			
	4 soft	0.071			
Pile type	1 cut	0.254	0.264	0.747	0.891
	2 loop	-0.370			
	3 high loop	-0.257			
	4 cut and loop	0.063			
Color pattern	1 dot	-0.021	0.452	0.529	
	2 square	-0.093			
	3 width	0.237			
	4 length	-0.221			
	5 diagonal	-0.038			
	6 none	0.022			
Pile pattern	1 dot	0.010	0.587	0.747	
	2 square	0.090			
	3 length	-0.601			
	4 diagonal	0.248			
	5 none	-0.199			
Basic pattern	1 length	0.216	0.191	0.753	
	2 width	-0.205			
	3 none	-0.156			

3.5.2 Analysis by rough set (RS) model

Table IV shows 12 sorted decision rules and its evaluation measures in order of higher coverage among more than 200 extracted ones by RS model. We extracted the decision rules with higher values than the thresholds of both certainty and coverage

measures. Threshold of certainty is the average probability 0.276 of “higher quality feeling” to all the samples. That of coverage is 0.18.

For example, the rule R3 indicates that if using the rule to configure new car floor carpet, it will give customers “higher quality feeling” with certainty 0.361. Coverage indicates the range of customers covered by the rule. In this rule, it is 21.1%. Thus, the rule R1 has the widest covering of customers, 23.1%, but its certainty is rather lower, 0.396. The rule with highest coverage is R1 which indicates that “diagonal in pile” element is important for “higher quality feeling” to product. Effect measure indicates the realistic effect of a rule normalized by the occurrence frequency of design element in samples. In the case, R6 has highest effect upon “ higher quality feeling”, 1.558.

Table IV. Decision rule for “higher quality feeling” and its evaluation measures

Design rule	Certainty	Effect	Coverage
R 1	0.396	1.433	0.231
R 2	0.395	1.429	0.228
R 3	0.361	1.308	0.211
R 4	0.361	1.308	0.211
R 5	0.361	1.308	0.211
R 6	0.430	1.558	0.188
R 7	0.424	1.534	0.185
R 8	0.424	1.534	0.185
R 9	0.417	1.510	0.182
R 10	0.417	1.510	0.182
R 11	0.417	1.510	0.182
R 12	0.417	1.510	0.182

Table V. Comparison of RS model and QT I

Design rule	Condition part				Quantification			
					D1	D2	D3	D4
R1	pile(diagonal)				**			
R2	pattern distance(60-90)	lockstech color(same pile length(wide)					*	
R3	basic color(brown)	color pattern (none)						
R4	basic color(brown)	pile color pattern (none)						
R5	brightness(high)	color pattern (none)						
R6	pattern distance(lengh)	max P length(10.0-13 pile length(wide)				**	*	
R7	heel pad(none)	overlock width(10)	pile pattern(low loop)	hidden loop(yes)	*		*	**
R8	heel pad color(none)	overlock width(10)	pile pattern(low loop)	hidden loop(yes)			*	**
R9	heel pad(none)	colors(two)	pile length(wide)		*		*	
R10	heel pad(none)	colors(two)	hidden loop(yes)		*		**	
R11	heel pad color(none)	colors(two)	pile length(wide)				*	
R12	heel pad color(none)	colors(two)	hidden loop(yes)				*	

Table V shows the content of each decision rule and the comparison between decision rules and QT I. Symbol “D1” to “D4” corresponds to a condition of a decision rule, respectively. Symbol “**” indicates strongly significant design elements suggested by QT I. For example, the decision rule R7 indicates that if a floor carpet includes “no heel pad”, “10 in overlock width”, “low loop in pile pattern” and “hidden loop”, then the floor carpet will give customers “higher quality feeling” with the certainty 0.424 and coverage 18.5%. Four conditions are “D1” to “D4”. In that case, “D1” indicates the first condition of rule “no heel pad”. Symbol “*” indicates that QT I also suggest “D1” is

weekly significant for “higher quality feeling”. We may compute decision rules for a combination of some kansei words, for example, “ higher quality feeling and clean”.

3.5.3 Rule filtering by experts

Product design experts filtered these rules in viewpoints of good design rule, and selected useful ones for new floor carpet design among more than 200 rules. Design experts selected R7 and R8 for designing higher quality product. The selected rules were more complicated and long condition rules. You should notice that these decision rules are nearly consistent with the results of QT1, but the decision rules by RS model include design elements not suggested by QT I. For example, the item of “overlock width” is not found out by QT and is included in R7 and R8. However, design experts pointed out that it is the item interacting with “pile pattern” and “hidden loop” found out by QT I. Moreover, through searching all the decision rules pointed out by product experts, we found that design experts tended to select many decision rules with lower coverage. For example, the experts selected the rules with condition “ more than 3 kinds in pile length” and “weak contrast in lockstitch color”. Its coverage was rather lower, 0.029. This suggests that design experts may like more specific design rules for product design.

4. Conclusion

We proposed a rough set based kansei engineering methodology. We have applied proposed methodology to a new car floor carpet development project for new car design, and we got much more interesting design rules. We pointed out that on the present research stage, it will give better solution to use both traditional methodology and rough set based methodology. Moreover, we found out that it is significant for product design experts to filter design rules. In near future work, further, we will refine our methodology by applying it to more product development.

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