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A Rough-sets Approach to Design Support for Traditional Crafts

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Abstract. Usually, information about our surrounding world is imprecise, incomplete or uncertain, especially when we are dealing with subjective things. Still, our way of thinking and deciding depends on the information at our disposal, which means that to draw proper conclusions we should be able to process uncertain or incomplete information. Rough-sets theory is a new mathematical approach to imperfect knowledge which has been applied in knowledge discovery, decision support, approximate reasoning and pattern recognition. This study proposes two multi-criteria analysis models, and also develops a web-based decision support system to support web-based sales by recognizing and proposing alternatives. Based on the simulation of the system, this study intends to provide design support using rough-sets theory. Finally a case study of traditional crafts is presented, aiming to expand sales, stimulate market expansion, and support new product development.

Introduction

Decision-making also might be regarded as a problem-solving activity, which is terminated when a satisfactory solution is reached. Therefore, decision-making is a reasoning or emotional process which can be rational or irrational, and can be based on explicit assumptions or tacit assumptions (Simon, 1977). A major part of decision-making involves the analysis of a finite set of alternatives described in terms of evaluative criteria. Then the problem might be to rank these alternatives in terms of how attractive they are to the decision makers when all the criteria are considered simultaneously. Solving such problems is the focus of Multi-Criteria Decision Analysis (MCDA) also known as Multi-Criteria Decision Making (MCDM). This area of decision making, although it is very old and has attracted the interest of many researchers and practitioners, is still highly debated, as there are many MCDA/MCDM methods which may yield very different results when they are applied on exactly the same data.

In reality, decision-making activities involve a large number of discrete alternatives, each alternative is defined by multiple attributes, and sometimes a large number of people are involved in the decision-making process. Thus, advanced technology is essential to support the process of decision-making. Scott-Morton first articulated the concepts involved in Decision Support Systems in the early 1970s, under the term "management decision system". He defined such systems as "interactive computer-based systems, which help decision makers utilize data and models to solve unstructured problems" (Scott-Morton, 1971). Another definition of DSS provided by Keen and Scott-Morton is as follows: DSS adds the intellectual resources of individuals with the capabilities of the computer to improve the quality of decisions. It is a computer-based support system for management decision makers who deal with unstructured problems (Keen & Scott-Morton, 1978).

In purchasing activities, eventually many customers make their final decision unconsciously and based on rather subjective factors. They purchase the product, which "feels" better, and are often unable to explain why. Taking this "feeling" into account already in the design process can give a substantial selling advantage. Rough set theory introduced by Pawlak in 1985 can be regarded as a new mathematical tool for imperfect knowledge, vagueness or imprecision. In other words, we see elements of the universe in the context of information available reverse about them. As a consequence, two different elements can be indiscernible in the context of the information about them and seen as the same. The Rough-sets theory is based on the premise that lowering the degree of precision in the data makes the data pattern more visible, whereas the central premise of the rough philosophy is that knowledge consists in the ability of classification. In other words, the Rough-sets approach can be considered as a formal framework for discovering facts from imperfect data. The results of the Rough-sets approach are presented in the form of classification or decision rules derived from a set of examples (Suraj, 2004), (Polkowski, 2002), (Walczak, 1999). The basic concepts of the Rough-sets theory are information system, indiscernibility relation, lower and upper approximations, accuracy of approximation, independence of attributes, core attributes, and classification, etc.(Pawlak, 1982, 1991, 2002)

Regarding this issue of Traditional Crafts in Japan, our primary purpose is to propose two distribution-based methods and develop a web-based interactive system to support sales staff in a shop or to support web-based sales by recognizing and proposing alternatives which fit the preferences of consumers. Based on the simulation of the system, this study intends to provide design support using Rough-sets theory. Finally, a case study of traditional crafts is presented aiming to expand sales, stimulate market expansion, and support new product development.

Problem Specification

Two methods will be implemented for Multi-Criteria Analysis of a discrete choice, namely a selection of a subset of items from a given set of alternatives. This approach requires specification of alternatives, and experts or users can define such alternatives by evaluating or collecting values of attributes.

An alternative is an entity that represents a possible result of Multi-Criteria Analysis. In different approaches or contents, an alternative is also called a solution, an item, an object, a scenario, etc. We denote an alternative set by O, and assume it is defined by the corresponding set of attributes q_i. Thus, the set of alternatives O is defined by Eq. 1:

$$O = \{o_i, i = 1, \ldots, m, i \in I, m = \|I\|\} \tag{1}$$

where I is the set of subscripts indexing alternatives, and $\|I\|$ is equal to the number of elements of the set I. For the Kutani-ware problem an alternative is a given product; the set O is therefore composed of all considered Kutani-ware items.

An attribute is an element of a set, which characterizes an alternative. In a traditional, typical approach to MCA (Multi-Criteria Analysis), such a characteristic is composed of a vector of values. The attributes of our Kutani-ware selection problem can be specified as a matrix Q of values, where rows correspond to the alternatives, and columns correspond to attributes specifying the alternatives. Thus, an element q_{ij} of the matrix defines the value of the i-th alternative of the j-th attribute, called "kansei profile" shown in Eq. 2, later will be used to rank or classify the given set of alternatives.

$$q_i = \{q_{ij}, j = 1, \ldots, n, j \in J, n = \|J\|\} \tag{2}$$

where J is the set of subscripts indexing attributes, and $\|J\|$ is equal to the number of elements of the set J.

As mentioned above, the problem we are going to approach involves multiple discrete alternatives, each of which is defined by multiple pairs of attributes. A large number of experts were invited to make individual evaluations; all of these imply that it is a multi-expert/multi-criteria decision-making problem. Multi-Criteria Decision Analysis (MCDA) deals with finding an optimal solution or a set of solutions for a problem characterized by a vector of outcomes. The individual outcomes are rescaled to some uniform measures of achievement. Thus the role of component achievement function (CAF) is to measure the user satisfaction level related to each possible criterion value. Finally the outcomes are aggregated through a definition of the scalarizing function (SF) into a final scalarization. Different MCA methods use different aggregations (measuring the total, the average, the worst component achievement function, etc). The problem is how to select the best alternative, or how to rank or classify all alternatives responding to the preferences of a decision maker (how to define the individual CAF and SF). We implement two methods in the next section.

As mentioned earlier, we assume we have two sets of knowledge; one is from consumers, namely consumers' preferences specified through a small set of adjectives; the other is from experts, through a Kansei Evaluation experiment. Our methods and web-based system provide a link between the two sets of knowledge, and an interactive process for decision-making. Regarding the Kansei Evaluation experiment, a pre-study was conducted beforehand to collect kansei data of the products to be evaluated, in which products were assessed according to attributes by means of the Semantic Differential method (Osgood, et. al, 1957) and linguistic variables (Zadeh, 1975, 2005). A questionnaire was designed by means of the SD method to collect subjective assessments provided by a number of experts. The questionnaire consists of a listing of 26 pairs of attributes including kansei and context attributes, with a 7-point odd qualitative scale, which can be 5-point scale (Nakamori & Ryoke, 2006) (Yan, et. al, 2008) (Huynh, et. al, 2009). To help experts easily express their subjective assessments, for the pair of terms [*soft--hard*], we have the linguistic variables [*very soft, a little soft, neither soft nor hard, a little hard, hard, very hard*] to linguistically assess the products to be evaluated. The result of the evaluation experiment was summarized into distribution values, which will be used directly instead of making models. Fig. 1 shows the distribution value for the pair of words [soft-hard].

Figure 1 Distribution value for pair [*soft-hard*]

Target-Oriented Multi-Criteria Modeling

Original target-oriented decision model presumes that the decision maker has a monotonically increasing target preference. However indeed there are 3 types of preferences, "the more the better", "the less the better" and "too much or too little is not acceptable". The key idea of these target-oriented decision models is to use the cumulative distribution function and the level set of the probability distribution function in the target-oriented decision model, and in many situations, multiple attributes are of interest (Bordley & Kirkwood, 2000) (Keeney & Raiffa, 1976). In these models, scalarizing function is used to aggregate partial target achievements while assuming the mutual independence of different targets. However, it is recognized that in many decision problems attributes are mutually interdependent; sometimes, making models based on the original data causes information loss problem. We propose function $c^t(x)$, where $t = T_1, T_2, T_3, T_4, T_5, T_6, T_7$, to solve the interdependence problem among different targets and the information loss problem, by setting several sets of coefficients. For $t = T_1$, the set of coefficients is [1.0, 0.67, 0.33, 0.0, -0.33, -0.67, -1.0], where 1.0 defines the strongest relationship between target 1 and itself, -1.0 defines the weakest relationship between target 1 and target 7, and 0.0 defines no relationship between target 1 and target 4. Similarly, for $t = T_2$, the coefficient set is [0.6, 1.0, 0.6, 0.2, -0.2, -0.6, -1.0], for $t = T_3$, it is [0.0, 0.5, 1.0, 0.5, 0.0, -0.5, -1.0], for $t = T_4$, it is [-1.0, -0.33, 0.33, 1.0, 0.33, -0.33, -1.0], for $t = T_5$, it is [-1.0, -0.5, 0.0, 0.5, 1.0, 0.5, 0.0], for $t = T_6$, it is [-1.0, -0.6, -0.2, 0.2, 0.6, 1.0, 0.6], and for $t = T_7$, it is [-1.0, -0.67, -0.33, 0.0, 0.33, 0.67, 1.0]. Fig. 2 shows the pictures of the cups and plates used in the experiment; Fig. 3 shows the diagram of the function $c^t(x)$. The coefficient sets for all targets will be used for calculating the individual component achievement functions later.

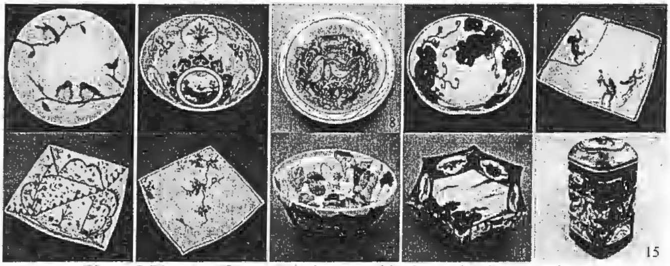

Figure 2 Pictures of cups and plates used in the evaluation experiment

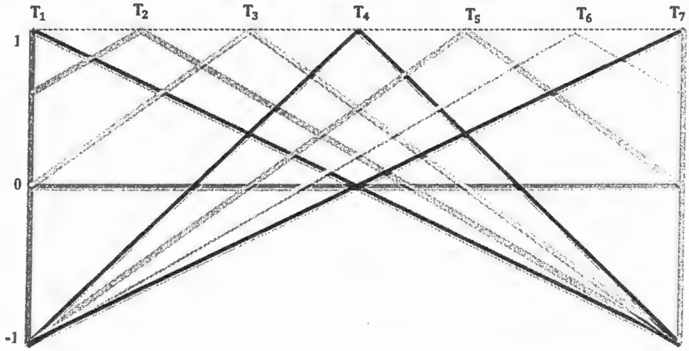

Figure 3 The diagram for function $c^t(x)$

As mentioned earlier, the role of individual component achievement function (CAF) is to measure the user satisfaction level related to each possible criterion value in a common scale for all criteria. For the calculation of component achievement functions, we propose Eq. 3:

$$CAF_{ij} = \sum_{x=1}^{7} d_{ij}(x) \times c^t(x) \tag{3}$$

where $d_{ij}(x)$ denotes the cumulative distribution function for attribute j, and $c^t(x)$ denotes the function for target t, $t = T_1, T_2, T_3, T_4, T_5, T_6, T_7$. The individual outcomes are transformed into a uniform scale of individual achievements; finally they are aggregated through a definition of the scalarizing function (SF) into a final scalarization. For the calculation of scalarizing function, we propose Method 1 and Method 2 shown in Eq. 4-6:

For Method 1:

$$SF_i = \min_j CAF_{ij} \tag{4}$$

For Method 2:

$$SF_i = = \min_j CAF_{ij} + 0.1/\|J\|\left(\sum_{j\in J} CAF_{ij}\right) \tag{5}$$

For both Method 1 and Method 2:

$$i^* = arg\,max_{i\in I}\, SF_i \tag{6}$$

where $\|J\|$ is the number of the selected criteria. For both Method 1 and Method 2, all the alternatives will be ranked in decreasing order of i^*, as shown in Eq. 6. Method 1 takes a "max-min" approach, while Method 2 considers the relationships among the interdependent targets. For the implementation and the evaluation of the two methods, we developed a web-based interactive system for the Traditional Crafts problem; the details of the system are stated in the next section.

A Decision Support System

Regarding the customers' preferences, which are specified through a small set of adjectives, we developed a web-based interactive system to support decision makers to select the Traditional Crafts they desire. At the same time, we asked users to evaluate which method is better during operation of the system, with respect to their satisfaction level regarding the recommended results. There are several layers in our system; they are "Home", "Problem", "Instance" and "Analysis" layers, respectively. In the "Home" layer which is shown in Fig. 4, users can access this system using a ID and password pair.

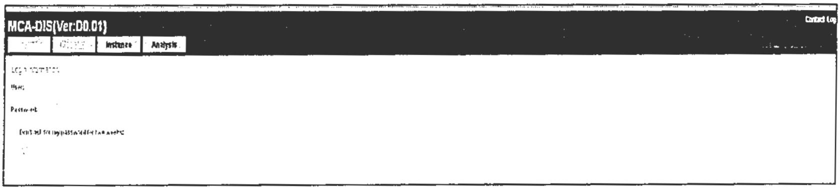

Figure 4 The "Home" layer

After logging into the system, the "problem" layer appears as in Fig. 5. In this layer, users can create personal problems, which are shown with ID, name, creator, and several other operations. For one problem, the creator can create multiple instances. We created one problem, concerning Kutani-ware, a famous Traditional Craft in Ishikawa Prefecture in Japan, shown in Fig. 5. To create instance/instances for this problem, just click "instance" and then the "instance" layer appears as shown in Fig. 6.

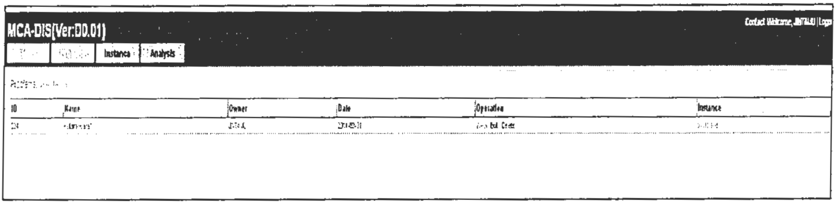

Figure 5 The "Problem" layer

In the instance layer, we created two instances for the Kutani-ware problem, one for test and the other for simulation. We can view the created instances, and of course create a new instance for this problem. For analysis of the created instances, just click "analysis". Here we analyze the "simulation" instance and "run" the system shown in Fig. 7.

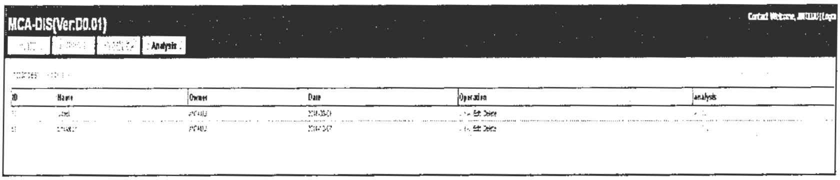

Figure 6 The "Instance" layer

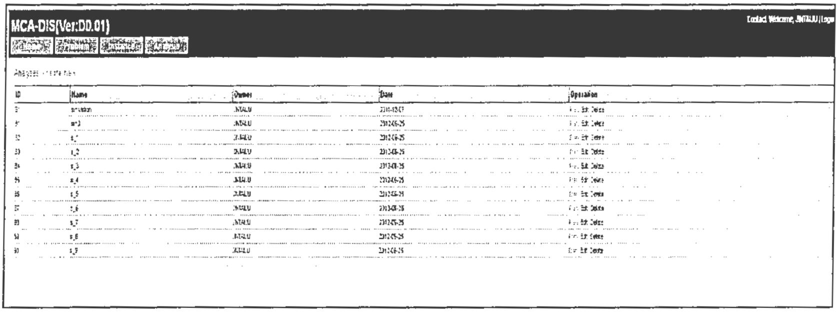

Figure 7 The "Analysis" layer

The following figures Fig. 8 and 9, show the main screen of the system. On the left-hand side, we have several options for users to assess their personal preferences about the products, for instance the size, the price or the type of the products. Additionally, we have a panel of adjective terms containing both kansei attributes and context attributes for assessing user preferences. The adjective terms are in pairs with an 8 scale of linguistic variables. Taking [soft-hard] as an instance; the linguistic variables are [*ignore, very soft, soft, a little soft, neither soft nor hard, a little hard, hard, very hard*]. After assessing the preferences, the recommendations were shown on the right-hand side of Fig. 8 and 9, correspondingly. Top 3 recommendations are cups or plates with hit graphs of each attribute, in which the red color indicates the selected target. The system records all iterations with iteration ID. For more simulations, we recommend here a web-based simulation system developed jointly with IME project members in IIASA, http://www.ime.iiasa.ac.at/mca_dis/.

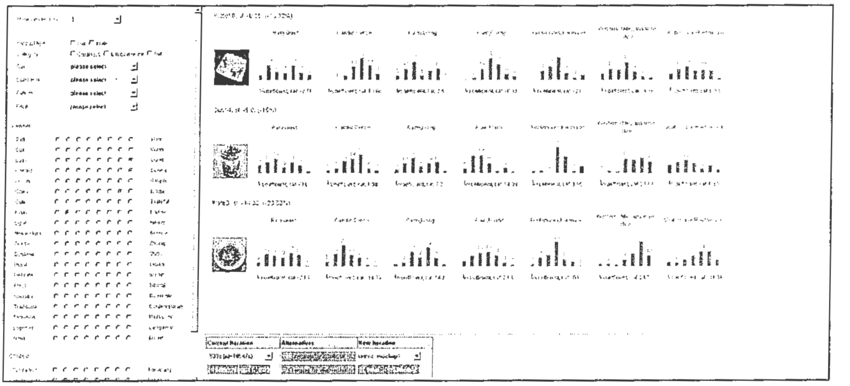

Figure 8 Screen for Method 1

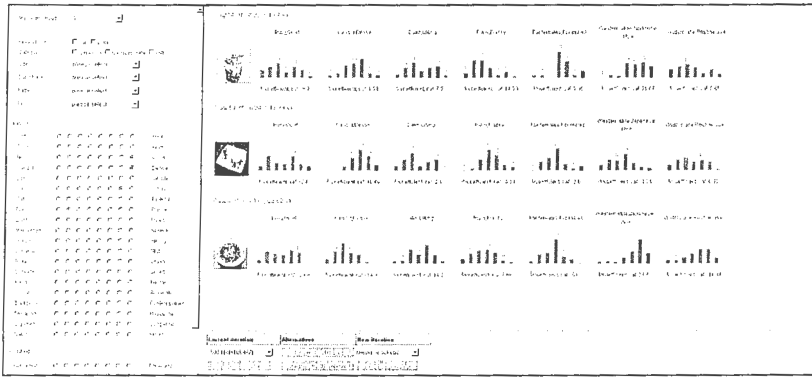

Figure 9 Screen for Method 2

Design Support for Kutani-ware Based-on Simulation Data

We asked a group of potential consumers to operate the system and try to satisfy their preferences using our models. At the same time, considering all the possibilities of consumer preferences, we developed a simulator based on random operation, and here we describe the functionality of the simulator from a software engineering point of view, namely, what the simulator does. The simulator selects 3-5 attributes from the 26 conditional attributes (20 Kansei attributes and 6 context attributes) and the level of each attribute in a range of [0, 1, 2, 3, 4, 5, 6] randomly; then it runs the models, and finally stores the top 3 results. The real implementation of the simulation in each iteration generates 26 random numbers in a range of [0,1] corresponding to each attribute, for example, 0.48 for [soft], 0.32 for [cool], 0.78 for [busy], 0.01 for [candid], 0.32 for [luxury], 0.45 for [cute], 0.32 for [plain], 0.97 for [light], 0.13 for [momentum], 0.45 for [gentle], 0.49 for [dynamic], 0.12 for [rural], 0.34 for [delicate], 0.67 for [fresh], 0.13 for [sociable], 0.24 for [traditional], 0.32 for [feminine], 0.13 for [dignified], 0.87 for [naive], 0.43 for [senior], 0.33 for [females], 0.23 for [western style], 0.11 for [use myself], 0.11 for [visitors' use], and 0.23 for [souvenir]; then selects the top 3 high values. If the fourth highest value is greater than (26-3)/26, then we select it as the fourth attribute, if the fifth highest value is greater than (26-4)/26, then we select it as the fifth attribute, in this example the fourth highest value is 0.67 for fresh < (26-3)/26, so the top 3 attributes are selected as 0.97 for [light], 0.87 for [naive], and 0.78 for [busy]; then selects the level for each attribute. If $(i/7 =< a < (i+1)/7)$ then $(attribute = i+1, i=0,1,\ldots,6)$, in this example, 4 for [light], 1 for [naive], and 2 for [busy]. For values larger than 4, we code them as 1, which means selected by consumers. For values smaller than 4, we code them as 0, which means not selected by consumers; then runs the model many times and finally exports the results in an Excel format file from the database. Figure 10 shows the physical information of all the alternatives, which will be used as decisional attributes in the later analysis. Figure 11 shows the output of the simulation for only 100 times. Letters a to z denote the 26 conditional attributes, capital D denotes the decision attributes. In order to use Rough-sets software, we coded Figure 11 into Figure 12 based on the principles: for both conditional attributes and decision attribute, 0 is coded as 2, and 1 is coded as1.

	samples	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12	D13	D14
cups	1	0	0	0	0	0	1	0	1	0	0	0	1	1	0
	2	0	0	0	0	1	0	0	1	0	0	0	1	1	0
	3	0	0	0	1	0	0	0	0	1	1	0	0	0	0
	4	0	0	0	0	0	1	0	1	0	1	0	0	1	0
	5	0	0	0	1	0	0	0	1	0	1	0	0	0	1
	6	0	0	0	1	0	0	1	0	0	1	0	0	0	0
	7	0	0	0	0	1	0	0	1	1	0	1	0	0	0
	8	0	0	0	0	0	1	1	0	0	0	0	1	0	0
	9	0	0	0	0	1	0	1	0	0	1	0	0	0	0
	10	0	0	0	1	0	0	0	1	0	1	0	0	0	0
	11	0	0	0	0	0	1	1	1	1	0	0	1	0	0
	12	0	0	0	0	1	0	0	1	0	1	0	1	0	0
	13	0	0	0	1	0	0	0	0	1	0	1	0	0	1
	14	0	0	0	0	0	1	0	0	1	1	0	0	1	0
	15	0	0	0	0	1	0	1	0	0	0	0	1	0	1
plates	16	1	0	0	1	0	1	0	1	0	1	0	0	0	0
	17	0	1	0	1	1	1	0	0	1	0	1	0	0	0
	18	1	0	0	1	0	0	0	1	0	1	0	0	0	0
	19	1	0	0	0	1	0	1	1	0	1	0	0	0	0
	20	0	0	1	0	0	1	1	1	1	0	0	1	0	0
	21	1	0	0	0	1	0	1	1	0	1	0	0	0	0
	22	1	0	0	0	0	1	1	1	1	0	1	0	0	0
	23	1	0	0	0	0	1	1	1	0	0	1	0	0	0
	24	1	0	0	0	1	0	0	1	0	0	1	0	0	0
	25	0	1	0	0	1	0	0	0	1	1	0	0	0	0
	26	0	1	0	1	0	0	0	1	1	1	0	0	0	0
	27	0	1	0	0	0	1	0	1	0	1	0	0	0	0
	28	1	0	0	0	0	1	0	1	0	1	0	0	0	0
	29	0	0	1	0	1	0	0	1	0	0	0	1	0	0
	30	0	1	0	0	1	0	0	1	0	0	0	1	0	0

Figure 10 Physical information of alternatives

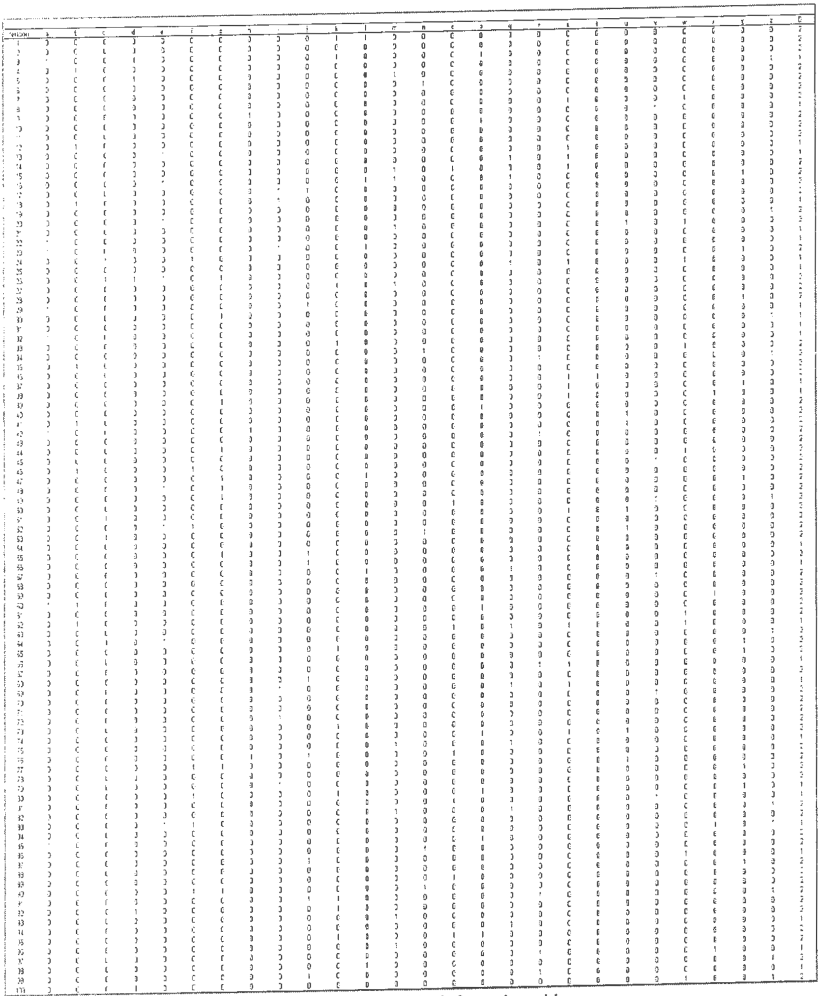

Figure 11 A part of the information table

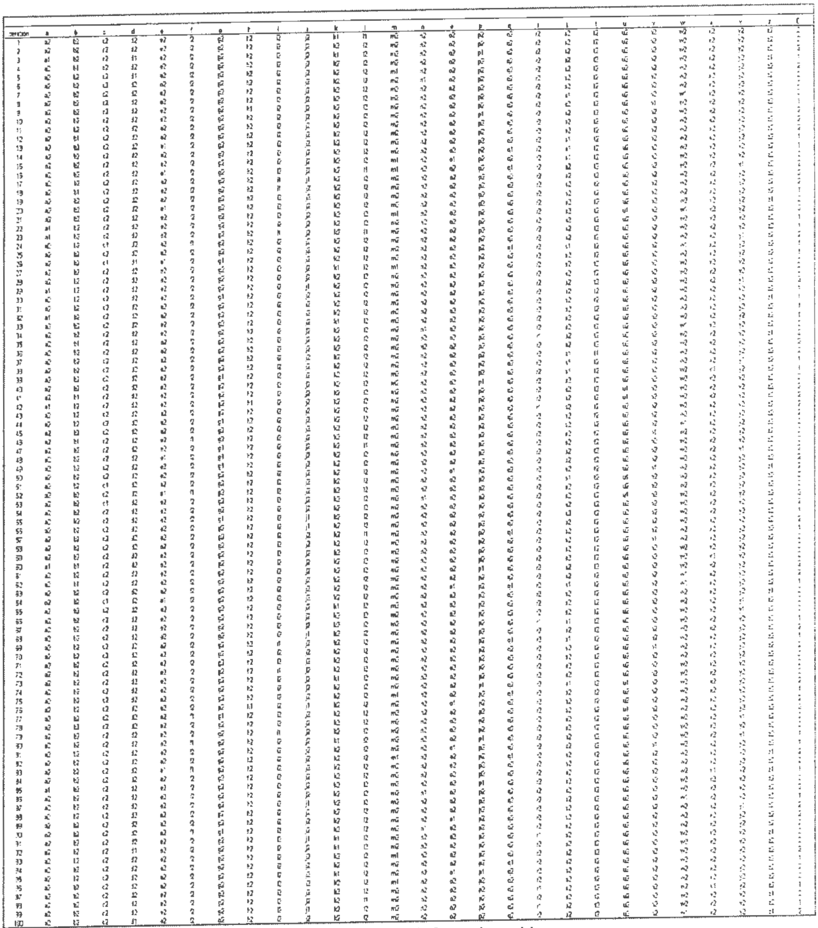

Figure 12 Coded information table

For the convenience of calculation, we developed software based on Rough-sets theory, and the calculation results are attached in the Appendix. Here we enumerate the abstracted rules which have a CI > 0.005:

If (*contemporary*) and (*souvenir*) and (*flashy*), then (*Hexagon*), CI=0.0072
If (*fresh*) and (*static*) and (*for males*), then (*Hexagon*), CI=0.0054
If (*souvenir*) and (*simple*) and (*lilting*), then (*Hexagon*), CI=0.0054
If (*warm*) and (*dynamic*), then (*Cool color*), CI=0.0057
If (*fresh*) and (*for senior*), then (*Flowers*), CI=0.0051

Subjective Evaluation

This study performed a case study regarding Kutani-ware for the purpose of stimulating the marketing of traditional crafts by utilizing high technology. From the authors' point of view, the recommendations by the proposed approach are very reasonable. However, feedback regarding the new approach from a majority of consumers is essential. In order to develop this study into real practice, we performed subjective evaluation of our system by demonstrating the recommendation system. We asked a group of people including students and craft shop owners, to score the satisfaction levels of their random requriements on a scale of 1 to 5 points upon a set of attributes *[favorability, utility, reliablity, operationality, understandability, viewability and speed]*. Finally we obtained an average score of 4.67, which means the developed decision support system is successful. We also planned to compare our proposed methods with other approaches like probability approach, fuzzy approach, etc. However because of time limatations, we only performed the comparison between our two proposed methods by asking consumers about their satisfaction levels regarding the recommendations of the two methods roughly, and the results show Method 2 is better than Method 1. Regarding the evaluation of the abstracted rules, we asked a group of designers who are well-experinced in the design of Traditional Crafts. They accepted the abstracted rules and planned to implement them into real design activities.

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