A Target-Based Decision-Making Approach to Consumer-Oriented Evaluation Model for Japanese Traditional Crafts

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***Abstract*—This paper deals with the evaluation of Japanese traditional crafts, in which product items are assessed according to the so-called "Kansei" features by means of the semantic differential method. For traditional crafts, decisions on which items to buy or use are usually influenced by personal feelings/characteristics; therefore, we shall propose a consumer-oriented evaluation model targeting these specific requests by consumers. Particularly, given a consumer's request, the proposed model aims to define an evaluation function that quantifies how well a product item meets the consumer's feeling preferences. An application to evaluating patterns of Kutani porcelain is conducted to illustrate how the proposed evaluation model works, in practice.**

***Index Terms*—Consumer-oriented evaluation, decision analysis, kansei data, ordered weighted averaging (OWA) operator, recommendation, traditional craft.**

I. Introduction

NOWADAYS, consumers and customers are more demanding, not only regarding quality but also regarding their satisfaction in terms of psychological feelings about products and services to be purchased. They have become much more selective in their choices. Therefore, in an increasingly competitive world market, it is important for manufacturers to have a customer-focused approach in order to improve attractiveness in the development of new products, which should not only satisfy the requirements of physical quality, defined objectively, but also the consumers' psychological needs, by essence subjective [37]. This approach has actually received much attention since the 1970s from the research community of consumer-focused design and Kansei engineering. Particularly, Kansei engineering, defined as "translating technology of a consumer's feeling and image for a product into design elements" [27], has been developed and successfully applied to a variety of industries [28], [41]; especially in Japan, it has been widely applied to the product design process in industries such as automotive, home electronics, office machines, cosmetics, food and drink, packaging, building products, and other sectors [10]. *Kansei* is a Japanese term reflecting a multifaceted expression that is closely connected to Japanese culture and so has no direct corresponding word in English or other languages. According to M. Nagamachi, the founder of Kansei engineering, *kansei* is "the impression somebody gets from a certain artifact, environment or situation using all her senses of sight, hearing, feeling, smell, taste [and sense of balance] as well as their recognition," as quoted from [41]. For building a kansei database on psychological feelings regarding products, the most commonly used method is to choose (adjectival) kansei words first, and then ask people to express their feelings using these kansei words by means of the semantic differential (SD) method [36] or its modifications, e.g., [11], [20], [30], and [41].

In this paper, we focus on the evaluation of traditional craft products using kansei data, taking consumer-specified preferences on kansei features of traditional products into consideration. These evaluations would be helpful for marketing or recommendation purposes [21], and would be particularly important in the era of e-commerce, where recommendation systems have become an important research area [1]. It should be emphasized here that artistic and aesthetic aspects play a crucial role in perception of traditional crafts, and therefore, kansei data are essential and necessary for evaluation. Also note that many studies of Kansei engineering or other consumer-oriented design techniques have involved an evaluation process in which, for example, a design could be selected for production [37]. However, Kansei-based evaluations[1] of existing products have generally received less attention [25], in particular, for traditional craft products.

Generally, evaluations for ranking and selection are two closely related, common facets of human decision-making activities, in practice. So far, decision analysis approaches have been widely applied to a variety of evaluation problems in the literature [5], [7], [26], [37]–[40], [42], [51]. Particularly, in the area of engineering management, Sarkis and Sundarraj [40] have developed a decision model for high-level assessment of enterprise information technology systems. Chu *et al*. [7] proposed to use a nonadditive fuzzy integral-based decision model for performance assessment of organizational transformations in enhancing a firm's core competencies. Shang *et al*. [39] have developed a multicriteria decision model for evaluation of transportation projects, while Zhou *et al*. [51] and Sun *et al*. [42] have

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[1]Here, by a "Kansei-based evaluation," we mean an evaluation using kansei data of subjective feelings.

applied group decision support models for journal quality assessment and evaluation of experts in R&D project selection, respectively. Here, in the present paper, we aim at proposing and developing an evaluation model for Japanese traditional crafts using kansei data and consumer-specified preferences, making use of the fuzzy target-based decision model that was recently developed by Huynh *et al*. [18].

In order to do so, as mentioned earlier, preliminary research was conducted to select kansei words, and then a population of subjects was gathered for collecting kansei assessment data of traditional crafts. The SD method was used as a measurement instrument. Using the voting statistics (as considered by, e.g., Balwin *et al.* [3] and Lawry [23] regarding the voting model semantics for linguistic variables [46]–[48]), these kansei assessment data are then used to generate kansei profiles of patterns to be evaluated; later, these profiles will eventually serve as the knowledge for a consumer-oriented evaluation. Because the preference on traditional crafts varies from person to person depending on personal character, feelings, and aesthetics, we will introduce a recommendation procedure that generates an evaluation function $V : \mathcal{O} \rightarrow [0,\ 1]$ at run time according to consumer's request and available kansei assessment data. Here, $\mathcal{O}$ is the set of evaluated patterns or objects and $V(o)$ is interpreted as the degree to which pattern o meets the consumer's preference. Basically, our approach is based on the appealing idea of target-based decision analysis [4], in which consumer is assumed to be interested only in patterns meeting her personal needs.

In a different, but similar context, Martínez [26] has recently proposed to use linguistic decision analysis for sensory evaluation based on the linguistic 2-tuple representation model [13]. Though the knowledge used for sensory evaluation is also acquired by means of human senses of *sight*, *taste*, *touch*, *smell*, and *hearing*, we want to use the term *Kansei-based evaluation* here, as its research context is closely linked to Japanese culture. In addition, Martínez's model considers the evaluation problem as a multiexpert/multicriteria decision-making problem, and assumes a consistent order relation over the qualitative evaluation scale treated as the linguistic term set of a linguistic variable [46]–[48]. Typically, Martínez's model yields an overall ranking of evaluated objects, which is clearly inappropriate for the purpose of personalized recommendations. By contrast, in our model, the preference order on the qualitative scale according to a kansei feature will be determined adaptively depending on a particular consumer's preferences. Note that the personal preference of consumers plays a strongly influential role in purchasing decisions of traditional arts and crafts. Furthermore, viewing multiperson assessments as uncertain judgments regarding kansei features of traditional craft items, a similar idea, as in uncertain decision making with fuzzy targets [18], can be applied to work out the probability that judgment on a kansei feature of each item meets the feeling target set on this feature by the consumer. Then, guided by the linguistic quantifier and also specified by the consumer, an appropriate ordered weighted averaging (OWA) operator [43] can be used to define the evaluation function V, as mentioned previously.

This paper is organized as follows. Section II begins with a brief description of the research context, and follows with the formulation of the research problem. Section III introduces a consumer-oriented evaluation model using kansei data, and Section IV applies the proposed model to a case study of evaluating Kutani porcelain, one of the traditional craft products of Ishikawa prefecture designated by the Japanese Ministry of Economy, Trade and Industry (METI). Finally, some concluding remarks are presented in Section V.

II. Research Problem and Formulation

A. *Traditional Craft Industries in Japan*

In Japan, there are a large number of traditional craft products that are closely connected to Japanese traditional culture. As explained on the Web site of The Association for the Promotion of Traditional Craft Industries,[2] each of traditional craft products is "unique fostered through regional differences and loving dedication, and provides a continual wealth of pleasure." However, due to the rapidly changing lifestyles of younger generations, and the prevalence of modern industrial products with their advantages in cost and usability, the market for traditional crafts in Japan has been shrinking over recent decades. In 1974, the Japanese government (METI) enacted the so-called Densan Law for the Promotion of Traditional Craft Industries,[3] as quoted next:

> Japan has a great number of items for daily use, whose development reflects the country's history, environment and lifestyle. Meanwhile, because of the factors such as changing lifestyle and the development of new raw materials, crafts manufactured with traditional methods and materials are having hard times. Under the circumstances, METI enacted the above law in May 1974 with the objective of promoting the traditional crafts industry in order that traditional crafts bring richness and elegance to people's living and contribute to the development of local economy, consequently, the sound development of nation's economy.

In addition, since 1984, METI has designated the month of November as the Traditional Crafts Month, and conducted publicity and educational programs related to traditional crafts throughout Japan. All of these attempts have been not only important from the economic perspective, but also particularly important from the cultural perspective in maintaining a spiritual heritage that makes the country unique.

However, with rapid growth of e-commerce in today's business, the Internet can be a great help in revitalizing traditional craft industries. Manufacturers and retailers, via their Web sites, can make their marketing better by providing a more attractive introduction and, hopefully, personalized recommendations, or even helping bring people back to the traditional and cultural values concerning their products. Interestingly, as reported in a recent Reuters' news article by Negishi [32], the kimono[4] market could impressively improve its situation of shrinking to less than half its size over the last two decades. This could be helped by a host of Web sites where online tips, for instance, on kimono

[2] http://www.kougei.or.jp/english/promotion.html
[3] http://www.kansai.meti.go.jp/english/dentousangyou/top_page.html
[4] Described as one of Japan's oldest works of art.

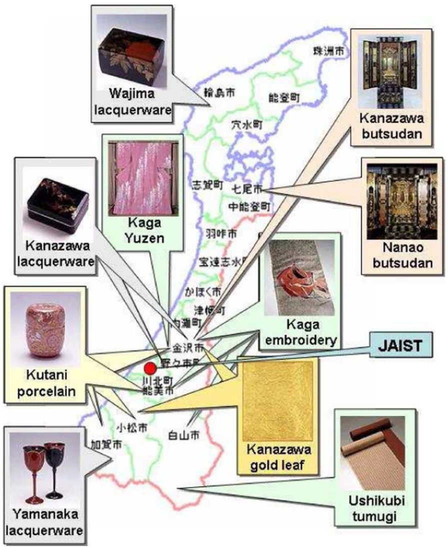

Fig. 1. Distribution of traditional craft products in Ishikawa, Japan.

wear and care, or on selecting the right pattern kimono, play a role.

Our main concern is about the consumer-oriented evaluation of Japanese traditional products for the personalized recommendation problem. A particular emphasis is laid on the evaluation of traditional craft products of Ishikawa Prefecture of Japan (see Fig. 1), where our institute, Japan Advanced Institute of Science and Technology (JAIST), is located.

B. Formulation of the Problem

The consumer-oriented evaluation process for traditional crafts using kansei data is graphically described in Fig. 2. Let us denote the collection of craft patterns to be evaluated by $\mathcal{O}$ and the cardinality of $\mathcal{O}$ by N, i.e., $N = |\mathcal{O}|$.

1) Identification of Kansei Features and Measurement Instrument: As mentioned previously, the first task in the Kansei-based evaluation process is to identify what kansei features people use to express their feelings regarding traditional crafts. In the present research project, kansei features are selected through a brainstorming process by relevant researchers, senior residents, and certified masters of traditional crafts. Each kansei feature is defined by a pair of opposing adjectives as kansei words, for example, the *fun* feature determines the pair of kansei words *solemn* and *funny*. Let:

1) $\{F_1, \ldots, F_K\}$ be the set of kansei features selected, and
2) $\mathbf{w}_k^+$ and $\mathbf{w}_k^-$ be the opposite pair of kansei words corresponding to F_k, for $k = 1, \ldots, K$. Denote $\mathbf{W}$ as the set of kansei words, i.e., $\mathbf{W} = \{\mathbf{w}_k^+, \mathbf{w}_k^- | k = 1, \ldots, K\}$.

Then, SD method [36] is used as a measurement instrument to design a questionnaire for gathering kansei data. It is of interest to mention here that the SD method has been widely used in applications such as for printers [6], microelectronics [8], mobilephones [9], office chairs [14], cars [15], [20], telephones [16], machine tools [25], table glasses [37], construction machinery [30], waterside environment [31], and mascot design [24], among others.

2) Gathering Information: The questionnaire using SD method for gathering information consists of listing the kansei features. Each kansei feature corresponds to an opposite pair of kansei words that lie at either end of a qualitative M-point scale, where M is an odd positive integer as used, for example, in 5-point scale [31], 7-point scale [25], or 9-point scale [22]. In our model, the qualitative scale is treated as a categorical scale, then we symbolically denote the M-point scale by

$$\mathbb{V} = \{v_1, \ldots, v_M\}$$

where $\mathbf{w}_k^+$ and $\mathbf{w}_k^-$ are, respectively, assumed to be at the ends v_1 and v_M, as illustrated in Fig. 3.

The questionnaire is then distributed to a population $\mathcal{P}$ of subjects, who are invited to express their emotional assessments according to each kansei feature of craft patterns in $\mathcal{O}$ by using the M-point scale. Formally, we can model the kansei data of each craft pattern $o_i \in \mathcal{O}$ according to kansei features obtained from the assessment of subjects S_j in $\mathcal{P}$, as shown in Table I, where $x_{jk}(o_i) \in \mathbb{V}$, for $j = 1, \ldots, P = |\mathcal{P}|$ and $k = 1, \ldots, K$.

3) Problem: Once the kansei assessment database has been built, as described before, it will be utilized to generate the so-called kansei profiles of patterns. Then these kansei profiles will be used as the knowledge for the following evaluation. Assume that a potential consumer is interested in looking for a craft pattern that would meet her preference given by a proper subset W of the set $\mathbf{W}$ of kansei words, as defined next. She may then want to rate craft patterns available in $\mathcal{O}$ according to her preference. In particular, we are concerned with consumer-specified requests that can be stated generally in the form of the following statement:

> "I like craft patterns which would best meet LQ (of) my preference specified in $W \subset \mathbf{W}$" (★)

where LQ is a linguistic quantifier such as *all*, *most*, *at least half*, *as many as possible*, etc. Formally, the problem can be formulated as follows.

Given $W = \{\mathbf{w}_{k_1}^*, \ldots, \mathbf{w}_{k_n}^*\}$ and LQ corresponding to the request specified by consumer as linguistically stated in (★), where $*$ stands for either $+$ or $-$, and $\{k_1, \ldots, k_n\} \subseteq \{1, \ldots, K\}$, the problem now is how to evaluate craft patterns in $\mathcal{O}$ using kansei data and the request specified as the pair $[W, LQ]$? Here, by $*$ that stands for either $+$ or $-$, as mentioned previously, we mean that only one of the two, $\mathbf{w}_{k_l}^+$ or $\mathbf{w}_{k_l}^-$ $(l = 1, \ldots, n)$, is present in W. This assumption would be psychologically reasonable. For example, if the consumer is interested in craft items that are *funny* according to the kansei feature "*fun,*" then she is not interested in those items that are *solemn*, the opposite of the kansei word *funny*.

This evaluation problem will be solved by a so-called consumer-oriented evaluation model presented in the next section.

III. Consumer-Oriented Evaluation Model

In this section, we shall propose a consumer-oriented evaluation model based on the idea that a consumer will probably be interested only in craft patterns that would best meet her

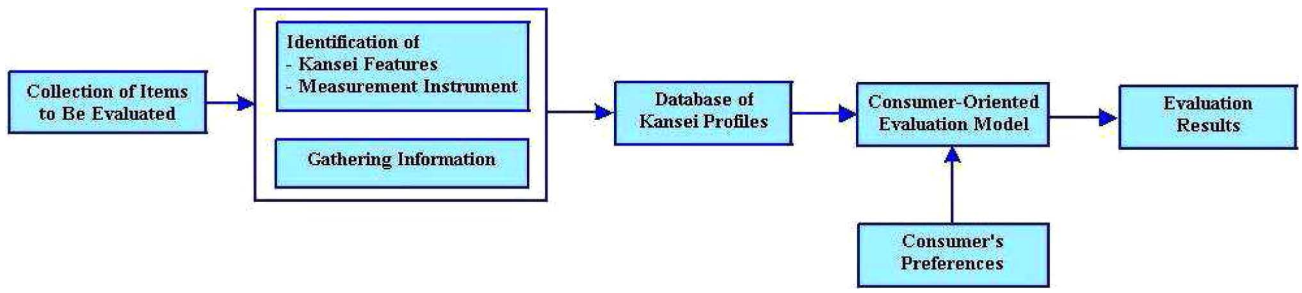

Fig. 2. Framework of consumer-oriented evaluation using kansei data.

F_k

$\mathbf{w}_k^+$	v_1	$\cdots$	v_M	$\mathbf{w}_k^-$

Fig. 3. Qualitative M-point scale for gathering kansei data.

TABLE I
KANSEI ASSESSMENT DATA OF PATTERN o_i

Subjects	Kansei Features			
	F_1	F_2	$\cdots$	F_K
S_1	$x_{11}(o_i)$	$x_{12}(o_i)$	$\cdots$	$x_{1K}(o_i)$
S_2	$x_{21}(o_i)$	$x_{22}(o_i)$	$\cdots$	$x_{2K}(o_i)$
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
S_P	$x_{P1}(o_i)$	$x_{P2}(o_i)$	$\cdots$	$x_{PK}(o_i)$

psychological needs from the aesthetic point of view. Let us denote the kansei assessment database about a finite set $\mathcal{O}$ of craft patterns by $\mathbf{D}$ and the data of pattern o_i $(i = 1, \ldots, N)$ by $\mathbf{D}[o_i]$, as shown in Table I. The proposed model basically consists of the following main steps. The first step is to generate a kansei profile for each pattern o_i using its data $\mathbf{D}[o_i]$. Then, in the second step, given the request specified by a consumer c as a pair $[W, LQ]$, an evaluation function $V : \mathcal{O} \to [0, 1]$ is defined taking c's request into consideration. Lastly, a ranking order for all patterns in $\mathcal{O}$ is determined according to this function V as an answer to the request. In the following, we will describe these three steps in detail.

A. Generating Kansei Profiles

For each pattern o_i with its assessment data $\mathbf{D}[o_i]$ shown in Table I, we define for each kansei feature F_k $(k = 1, \ldots, K)$ a probability distribution $f_{ik} : \mathbb{V} \to [0, 1]$ as follows:

$$f_{ik}(v_h) = \frac{|\{S_j \in \mathcal{P} : x_{jk}(o_i) = v_h\}|}{|\mathcal{P}|} \tag{1}$$

where $|\cdot|$ denotes the cardinality of the set. This distribution f_{ik} is considered as an uncertain judgment of craft pattern o_i according to kansei feature F_k. In the same way, we can obtain a K-tuple of distributions $[f_{i1}, \ldots, f_{iK}]$ regarding the kansei assessment of o_i and call the tuple the kansei profile of o_i. Similarly, kansei profiles of all patterns in $\mathcal{O}$ can be generated from $\mathbf{D}$.

It should also be emphasized here that in many papers regarding Kansei engineering or other methodologies of consumer-oriented design support, which also used the SD method for gathering data, populations of subjects involved in experimental studies have a size ranging typically from 10 to 35 people, (cf., [10], [22], [25], and [37]). However, for the purpose of consumer-oriented evaluation, which the present paper is aiming at, such a small size of the population $\mathcal{P}$ may cause a statistical bias, as well as may not provide enough information from the measurement of popularity. Therefore, a larger population of subjects has been used for gathering kansei data. In addition, in order to increase the reliability of subjective assessments, all subjects were required to participate in a centralized face-to-pattern evaluation session on a designated date. For example, in the case study of evaluating Kutani porcelain, a population of 211 subjects was used at a centralized evaluation session, as described in detail in Section IV.

B. Evaluation Function

Having generated kansei profiles for all patterns $o_i \in \mathcal{O}$, as mentioned before, we now define the evaluation function V corresponding to the request (★) symbolically denoted by $[W, LQ]$, where $W = \{\mathbf{w}_{k_1}^*, \ldots, \mathbf{w}_{k_n}^*\}$ and LQ is a linguistic quantifier.

Intuitively, if a consumer expresses her preference for a kansei feature such as *color contrast* with the kansei word *bright*, she might implicitly assume a preference order on the SD scale corresponding to *color contrast* toward the end v_1 where *bright* is placed. Conversely, if the consumer's preference for *color contrast* was *dark*, i.e., the opposite of the kansei word *bright*, she might assume a preference order on the scale toward the end v_M where *dark* is placed. In other words, in consumer-oriented evaluation using kansei data, the preference order on the SD scale corresponding to a kansei feature should be determined adaptively according to a particular consumer's preference. This can be formally formulated as mentioned next.

For each $\mathbf{w}_{k_l}^* \in W$, we define a complete preference order $\succeq_l$ on $\mathbb{V}$ according to the kansei feature F_{k_l} as follows:

$$v_h \succeq_l v_{h'} \Leftrightarrow \begin{cases} h' \geq h, & \text{if } \mathbf{w}_{k_l}^* = \mathbf{w}_{k_l}^+ \\ h \geq h', & \text{if } \mathbf{w}_{k_l}^* = \mathbf{w}_{k_l}^-. \end{cases} \tag{2}$$

In addition, due to vagueness inherent in consumer's expression of preference in terms of kansei words, each $\mathbf{w}_{k_l}^*$ is considered as the feeling target, denoted by T_{k_l}, of the consumer according to kansei feature F_{k_l}, which can be represented as a possibility variable [49] on $\mathbb{V}$ whose possibility distribution is defined as

$$\pi_{k_l}(v_h) = \begin{cases} \left(\frac{M-h}{M-1}\right)^m, & \text{if } \mathbf{w}_{k_l}^* = \mathbf{w}_{k_l}^+ \\ \left(\frac{h-1}{M-1}\right)^m, & \text{if } \mathbf{w}_{k_l}^* = \mathbf{w}_{k_l}^- \end{cases} \tag{3}$$

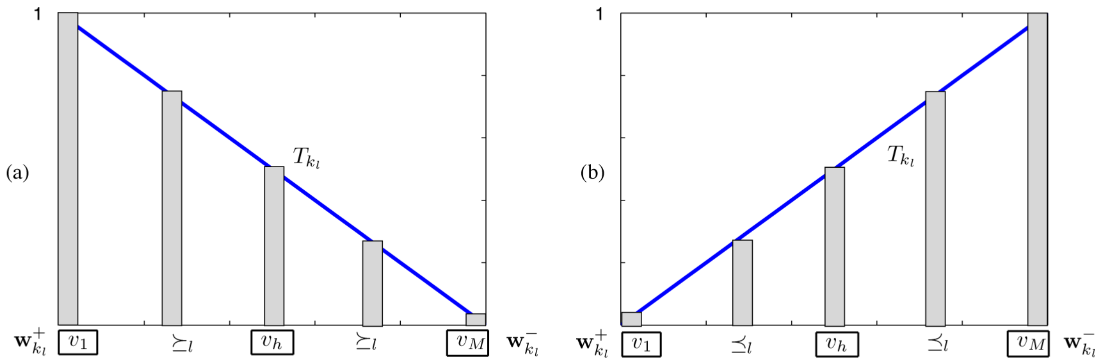

Fig. 4. Preference order $\succeq_l$ and the possibility distribution of feeling target T_{k_l}. (a) $\mathbf{w}^*_{k_l} = \mathbf{w}^+_{k_l}$. (b) $\mathbf{w}^*_{k_l} = \mathbf{w}^-_{k_l}$.

where $m \geq 0$ expresses the degree of intensity of the consumer's feelings about the target. Intuitively, when a consumer expresses her feeling targets using kansei words combined with linguistic modifiers such as *very*, *slightly*, etc., to emphasize her intensity about targets, the degree of intensity m can then be determined similarly as in Zadeh's method of modeling linguistic modifiers via power functions in approximate reasoning [46]–[48]. Fig. 4 graphically illustrates these concepts for the case $m = 1$, which exhibits a neutral intensity toward targets.

With the consumer's preference specified by W, we obtain n feeling targets T_{k_l} $(l = 1, \ldots, n)$ accompanying n preference orders $\succeq_l$ $(l = 1, \ldots, n)$ on the SD scale of kansei features F_{k_l} $(l = 1, \ldots, n)$, respectively. Recall that, for each $l = 1, \ldots, n$, the uncertain judgment of each craft pattern o_i regarding the kansei feature F_{k_l} is represented by the probability distribution f_{ik_l} over $\mathbb{V}$, as defined in (1). Bearing these considerations in mind, we are now able to evaluate how the feeling performance of a pattern o_i on F_{k_l}, denoted by $F_{k_l}(o_i)$, meets the feeling target T_{k_l} representing consumer's preference on F_{k_l}. This can be done as follows.

First, by making use of the possibility–probability conversion method [44], we can transform the possibility distribution of feeling target T_{k_l} into an associated probability distribution, denoted by $\hat{p}_{k_l}$, via simple normalization as follows:

$$\hat{p}_{k_l}(v_h) = \frac{\pi_{k_l}(v_h)}{\sum\limits_{v \in \mathbb{V}} \pi_{k_l}(v)}. \tag{4}$$

Then, by accepting the assumption that the feeling target T_{k_l} is stochastically independent of feeling performance on F_{k_l} of any pattern o_i, we can work out the probability that the feeling performance $F_{k_l}(o_i)$ meets the feeling target T_{k_l}, denoted by $\mathbf{P}(F_{k_l}(o_i) \succeq T_{k_l})$, in terms of the preference order $\succeq_l$ as

$$\begin{aligned}\mathbf{P}(F_{k_l}(o_i) \succeq T_{k_l}) &\triangleq P(f_{ik_l} \succeq_l \hat{p}_{k_l}) \\ &= \sum_{h=1}^{M} f_{ik_l}(v_h) P(v_h \succeq_l \hat{p}_{k_l}) \end{aligned} \tag{5}$$

where $P(v_h \succeq_l \hat{p}_{k_l})$ is the cumulative probability function defined by

$$P(v_h \succeq_l \hat{p}_{k_l}) = \sum_{v_h \succeq_l v_{h'}} \hat{p}_{k_l}(v_{h'}). \tag{6}$$

It is of interest to note here that a similar idea has also been recently used in [17] for developing the so-called satisfactory-oriented linguistic decision model. Intuitively, the quantity $\mathbf{P}(F_{k_l}(o_i) \succeq T_{k_l})$ defined before could be interpreted as the probability of "the feeling performance on F_{k_l} of o_i meeting the feeling target T_{k_l} specified by a consumer on F_{k_l}." Then, with these probabilities $\mathbf{P}(F_{k_l}(o_i) \succeq T_{k_l}) = \mathbf{P}_{k_l i}$, for $l = 1, \ldots, n$, we are able to aggregate all into an overall value by taking the linguistic quantifier LQ into account, making use of the so-called OWA aggregation operator [43].

An OWA operator of dimension n is a mapping

$$\mathcal{F} : [0, 1]^n \to [0, 1]$$

associated with a weighting vector $[w_1, \ldots, w_n]$ such that: 1) $w_l \in [0, 1]$ and 2) $\sum_l w_l = 1$, and

$$\mathcal{F}(a_1, \ldots, a_n) = \sum_{l=1}^{n} w_l b_l \tag{7}$$

where b_l is the lth largest element in the collection $a_1, \ldots, a_n$ and weights w_l can be obtained directly using fuzzy-set-based semantics of a linguistic quantifier LQ involved in the aggregation process (see Appendix I). Regarding the problem of multicriteria aggregation [43], if a_l denotes the degree to which an alternative meets someone's requirements at the lth criterion, then the aggregate value $\mathcal{F}(a_1, \ldots, a_n)$ indicates the degree to which the alternative meets someone's requirements with respect to the criteria.

Under such a semantics of OWA operators, we are now ready to define the evaluation function, for any $o_i \in \mathcal{O}$, as follows:

$$\begin{aligned} V(o_i) &= \mathcal{F}(\mathbf{P}_{k_1 i}, \ldots, \mathbf{P}_{k_n i}) \\ &= \sum_{l=1}^{n} w_l \mathbf{P}_{li} \end{aligned} \tag{8}$$

where $\mathbf{P}_{li}$ is the lth largest element in the collection $\mathbf{P}_{k_1 i}, \ldots, \mathbf{P}_{k_n i}$ and weighting vector $[w_1, \ldots, w_n]$ is determined directly by using a fuzzy-set-based semantics of the linguistic quantifier LQ (see Appendix I for more details). As interpreted previously on quantities $\mathbf{P}_{k_l i}$ $(l = 1, \ldots, n)$, the aggregate value $V(o_i)$, therefore, indicates the degree to which craft pattern o_i meets the feeling preference derived from the request specified by a consumer as $[W, LQ]$.

Input: A request $[W, LQ]$
- $W = \{\mathbf{w}^*_{k_1}, \ldots, \mathbf{w}^*_{k_n}\}$ – feeling preference.
- LQ – linguistic quantifier.

Output: A rating of all items in $\mathcal{O}$

```
for each w*_{k_l} ∈ W do
    determine the preference order ⪰_l on 𝕍 for kansei
    feature F_{k_l} via (2)
    determine the feeling target T_{k_l} on F_{k_l} and its possi-
    bility distribution via (3)
end for
determine weighting vector [w_1, ..., w_n] using the fuzzy
set-based semantics of linguistic quantifier LQ
for each o_i ∈ 𝒪 do
    for each w*_{k_l} ∈ W do
        compute P(F_{k_l}(o_i) ⪰ T_{k_l}) via (5)
    end for
    compute V(o_i) via (8)
end for
rank items o_i according to their values V(o_i)
```

Fig. 5. Recommendation procedure.

C. Rating Craft Patterns

Based on the evaluation function (8) defined before, a rating of all the craft patterns o_i in $\mathcal{O}$ can be straightforwardly determined according to their values $V(o_i)$ by a sorting algorithm for real numbers. The obtained rating is then considered as the recommendation to the request $[W, LQ]$.

For the sake of convenience, the evaluation procedure described before is summarized and algorithmically presented in Fig. 5.

In the following section, we shall apply this model to evaluating Kutani porcelain,[5] a traditional craft industry with a history dating back to the seventeenth century, of Kutani pottery village in Ishikawa Prefecture.

IV. Application to Kutani Porcelain

Within the framework of a research project supported by the local government, a total of 30 patterns of Kutani porcelain have been collected for Kansei-based evaluation, as photographically shown in Fig. 6.

Before gathering kansei assessment data of these patterns for evaluation, preliminary research was carried out to select kansei features, in consultation with local manufacturers and shops. Finally, 26 opposite pairs of kansei words were selected at the end of a brainstorming process. The answer sheet is actually in Japanese, using a qualitative 7-point scale. Kansei words are approximately translated into English, as shown in Table II.

A. Gathering Data and Kansei Profiles

Several assessment sessions, with a total of 211 subjects invited to participate, were held to gather kansei data. Among these 211 participants, 61.1% (129) were women and 38.9% (82) were men. The distribution of their ages is shown in Table III. The ratio of men and women, as well as the approximate age data of evaluators were considered, trying to match the ratio in the general Japanese population, but the selection of ages from early twenties to latter half of sixties is especially due to these age groups being targeted as potential customers.

The data obtained are three-way data of which each pattern Kutani#i ($i = 1, \ldots, 30$) is assessed by all participating subjects on all kansei features F_k, $k = 1, \ldots, 26$.

The three-way data are then used to generate kansei profiles for patterns via (1), as mentioned previously. These kansei profiles are considered as (uncertain) feeling assessments of patterns, serving as knowledge for consumer-oriented evaluation. For example, the kansei profile of pattern Kutani#10 is graphically shown in Fig. 7.

B. Consumer-Oriented Evaluation

To illustrate how the model proposed in the preceding section works, let us consider the following example.

Assuming a consumer's request is specified as

$$[\{\mathbf{w}_3^-, \mathbf{w}_7^+, \mathbf{w}_{11}^+, \mathbf{w}_{17}^+, \mathbf{w}_{25}^-, \}, \qquad \text{as many as possible}]$$

i.e., verbally, she would ask for craft patterns meeting *as many as possible* of her feeling preferences of *funny*, *pretty*, *flowery*, *bright*, and *pale*.

According to the evaluation procedure shown in Fig. 5, we first determine preference orders on $\mathbb{V} = \{v_1, \ldots, v_7\}$ for features F_3, F_7, F_{11}, F_{17}, and F_{25}. Using (2), we have $\succeq_3 = \succeq_{25}$ and $\succeq_7 = \succeq_{11} = \succeq_{17}$, where

$$v_7 \succeq_3 \cdots \succeq_3 v_1 \text{ and } v_1 \succeq_7 \cdots \succeq_7 v_7.$$

Then, using (3) for $m = 2$, we define feeling targets T_3, T_7, T_{11}, T_{17}, and T_{25} for features F_3, F_7, F_{11}, F_{17}, and F_{25}, respectively. For the sake of simplicity, we again have $T_3 \equiv T_{25}$ and $T_7 \equiv T_{11} \equiv T_{17}$ with possibility distributions shown in Figs. 8 and 9, respectively.

We now determine the weighting vector of dimension 5, denoted by $w = [w_1, w_2, w_3, w_4, w_5]$, according to the fuzzy-set-based semantics of linguistic quantifier "*as many as possible.*" Assume that, for example, the membership function of the quantifier "*as many as possible*" is defined as a mapping $Q : [0, 1] \to [0, 1]$ such that [12]

$$Q(r) = \begin{cases} 0, & \text{if } 0 \le r \le 0.5 \\ 2r - 1, & \text{if } 0.5 \le r \le 1. \end{cases}$$

We then obtain the weighting vector as $w = [0, 0, 0.2, 0.4, 0.4]$ using Yager's method proposed in [43] (refer to (14) in Appendix I).

With these preparations done, we are now ready to use (4) and (5) for computing probabilities $\mathbf{P}_{3i}$, $\mathbf{P}_{7i}$, $\mathbf{P}_{11i}$, $\mathbf{P}_{17i}$, and $\mathbf{P}_{25i}$ of meeting corresponding feeling targets T_3, T_7, T_{11}, T_{17}, and T_{25} for each pattern Kutani#i ($i = 1, \ldots, 30$). Then, using (8), we have

$$V(\text{Kutani\#}i) = \mathcal{F}(\mathbf{P}_{3i}, \mathbf{P}_{7i}, \mathbf{P}_{11i}, \mathbf{P}_{17i}, \mathbf{P}_{25i})$$

[5] http://shofu.pref.ishikawa.jp/shofu/intro_e/HTML/H_S50402.html

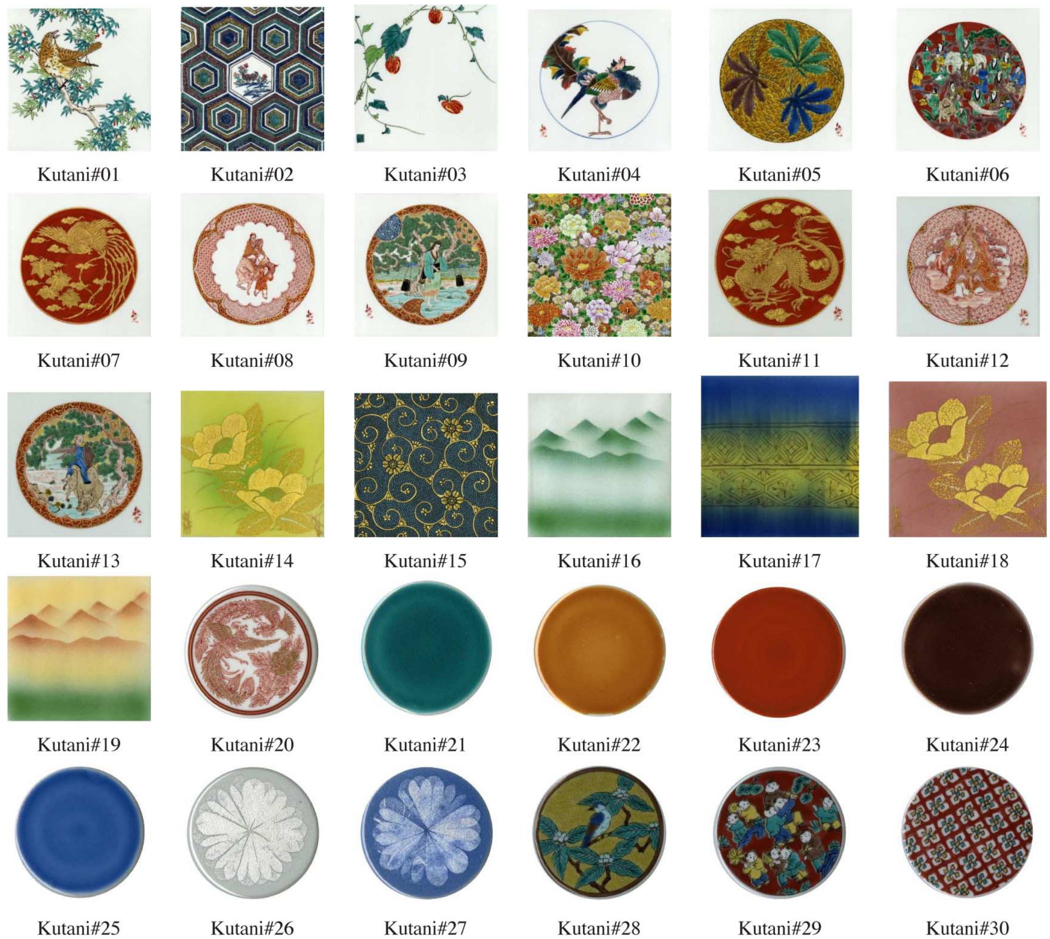

Fig. 6. Thirty samples of Kutani porcelain used for the evaluation.

TABLE II
OPPOSITE PAIRS OF KANSEI WORDS USED FOR THE EVALUATION

F_k	*Left kansei word*	v_1	v_2	v_3	v_4	v_5	v_6	v_7	*Right kansei word*
1	conventional ($\mathbf{w}_1^+$)	□	□	□	□	□	□	□	unconventional ($\mathbf{w}_1^-$)
2	simple ($\mathbf{w}_2^+$)	□	□	□	□	□	□	□	compound ($\mathbf{w}_2^-$)
3	solemn ($\mathbf{w}_3^+$)	□	□	□	□	□	□	□	funny ($\mathbf{w}_3^-$)
4	formal ($\mathbf{w}_4^+$)	□	□	□	□	□	□	□	casual ($\mathbf{w}_4^-$)
5	serene ($\mathbf{w}_5^+$)	□	□	□	□	□	□	□	forceful ($\mathbf{w}_5^-$)
6	still ($\mathbf{w}_6^+$)	□	□	□	□	□	□	□	moving ($\mathbf{w}_6^-$)
7	pretty ($\mathbf{w}_7^+$)	□	□	□	□	□	□	□	austere ($\mathbf{w}_7^-$)
8	friendly ($\mathbf{w}_8^+$)	□	□	□	□	□	□	□	unfriendly ($\mathbf{w}_8^-$)
9	soft ($\mathbf{w}_9^+$)	□	□	□	□	□	□	□	hard ($\mathbf{w}_9^-$)
10	boring ($\mathbf{w}_{10}^+$)	□	□	□	□	□	□	□	attractive ($\mathbf{w}_{10}^-$)
11	flowery ($\mathbf{w}_{11}^+$)	□	□	□	□	□	□	□	quiet ($\mathbf{w}_{11}^-$)
12	happy ($\mathbf{w}_{12}^+$)	□	□	□	□	□	□	□	unhappy ($\mathbf{w}_{12}^-$)
13	elegant ($\mathbf{w}_{13}^+$)	□	□	□	□	□	□	□	relaxed ($\mathbf{w}_{13}^-$)
14	delicate ($\mathbf{w}_{14}^+$)	□	□	□	□	□	□	□	strong ($\mathbf{w}_{14}^-$)
15	luxurious ($\mathbf{w}_{15}^+$)	□	□	□	□	□	□	□	frugal ($\mathbf{w}_{15}^-$)
16	gentle ($\mathbf{w}_{16}^+$)	□	□	□	□	□	□	□	pithy ($\mathbf{w}_{16}^-$)
17	bright ($\mathbf{w}_{17}^+$)	□	□	□	□	□	□	□	dark ($\mathbf{w}_{17}^-$)
18	reserved ($\mathbf{w}_{18}^+$)	□	□	□	□	□	□	□	outgoing ($\mathbf{w}_{18}^-$)
19	free ($\mathbf{w}_{19}^+$)	□	□	□	□	□	□	□	restricted ($\mathbf{w}_{19}^-$)
20	level ($\mathbf{w}_{20}^+$)	□	□	□	□	□	□	□	indented ($\mathbf{w}_{20}^-$)
21	lustrous ($\mathbf{w}_{21}^+$)	□	□	□	□	□	□	□	matte ($\mathbf{w}_{21}^-$)
22	transparent ($\mathbf{w}_{22}^+$)	□	□	□	□	□	□	□	dim ($\mathbf{w}_{22}^-$)
23	warm ($\mathbf{w}_{23}^+$)	□	□	□	□	□	□	□	cool ($\mathbf{w}_{23}^-$)
24	moist ($\mathbf{w}_{24}^+$)	□	□	□	□	□	□	□	arid ($\mathbf{w}_{24}^-$)
25	colorful ($\mathbf{w}_{25}^+$)	□	□	□	□	□	□	□	pale ($\mathbf{w}_{25}^-$)
26	plain ($\mathbf{w}_{26}^+$)	□	□	□	□	□	□	□	gaudy, loud ($\mathbf{w}_{26}^-$)

TABLE III
AGE DISTRIBUTION OF SUBJECTS PARTICIPATING IN THE EVALUATION PROCESS

Age	Number of subjects	%
20 to 29	56	26.5%
30 to 39	51	24.2%
40 to 49	51	24.2%
50 to 59	4	1.9%
≥ 60	49	23.2%
Total	211	100%

where $\mathcal{F}$ is the OWA operator of dimension 5 associated with the weighting vector $w = [0, 0, 0.2, 0.4, 0.4]$.

Finally, a ranking of patterns Kutani#i, $i = 1, \ldots, 30$, according to their values $V(\text{Kutani\#}i)$ can be easily obtained. Table IV shows the top three patterns that would best meet the feeling preferences *funny*, *pretty*, *flowery*, *bright*, and *pale* with different typical linguistic quantifiers used.

C. Analysis of the Obtained Results

For the sake of facilitating the discussion of obtained results, all the recommended patterns (according to typical linguistic quantifiers used), as well as their uncertain assessments on selected features F_3, F_7, F_{11}, F_{17}, and F_{25}, are depicted in Fig. 10. Accordingly, the target achievements of recommended patterns

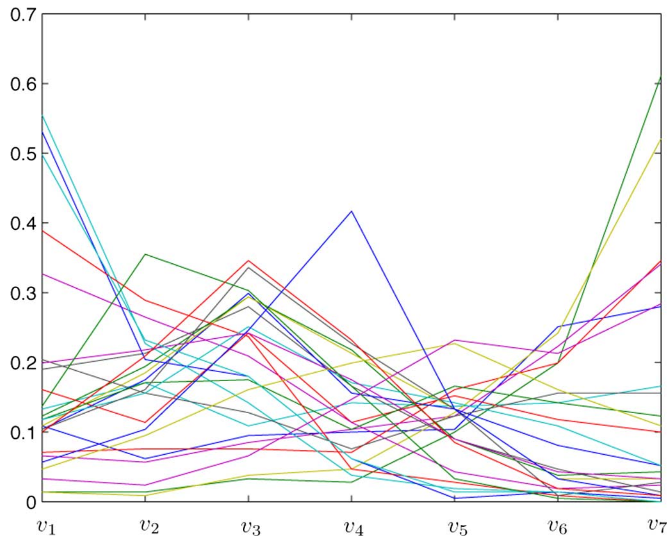

Fig. 7. Kansei profile of Kutani#10.

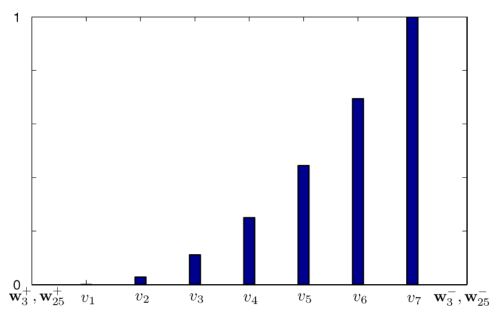

Fig. 8. Possibility distribution of feeling targets T_3 and T_{25} $(m = 2)$.

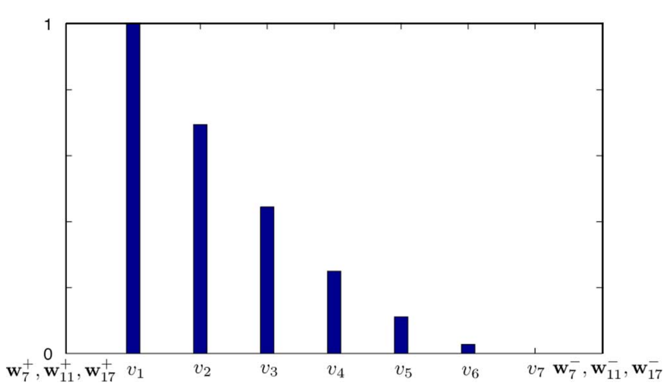

Fig. 9. Possibility distribution of feeling targets T_7, T_{11}, and T_{17} $(m = 2)$.

for selected features, as well as their aggregate values corresponding to different quantifiers used, are shown in Table V.

First, let us consider the results according to the use of the quantifier "*there exists*." As shown in Table IV, in this case, the top three patterns are, in order of preference, #10, #14, and #29. According to Table V and as graphically illustrated by Fig. 10, one can intuitively observe that pattern #10 very well meets the feeling target *flowery* $(\mathbf{w}_{11}^{+})$, followed by *bright* $(\mathbf{w}_{17}^{+})$ of

TABLE IV
QUANTIFIERS USED AND CORRESPONDING TOP THREE PATTERNS

Linguistic quantifier	Weighting vector	The top 3 patterns
As many as possible (AMAP)	$[0, 0, 0.2, 0.4, 0.4]$	#10 $\succeq$ #14 $\succeq$ #18
All	$[0, 0, 0, 0, 1]$	#27 $\succeq$ #30 $\succeq$ #29
There exists	$[1, 0, 0, 0, 0]$	#10 $\succeq$ #14 $\succeq$ #29
At least haft (ALH)	$[0.4, 0.4, 0.2, 0, 0]$	#10 $\succeq$ #14 $\succeq$ #29

pattern #14 and *funny* $(\mathbf{w}_3^{-})$ of pattern #29. In the case where quantifier "*at least half*" is used instead of "*there exists*," we still obtain the same result because, besides the feeling target *flowery*, pattern #10 has well met targets *funny* and *bright* too; moreover, besides *bright* and *funny*, both patterns #14 and #29 are quite good at *pretty*. It would be worth noting here that aggregation operator $\mathcal{F}$ with weighting vector corresponding to quantifier "*there exists*" is a pure "OR" operator, and the one corresponding to quantifier "*at least half*" still behaves like an "OR"-type aggregation as well; namely, the degree of "*orness*" (refer to (15) in Appendix I) associated with the operator $\mathcal{F}$ of quantifier *at least half* is

$$\text{orness}(\mathcal{F}) = \frac{1}{4}(4 \times 0.4 + 3 \times 0.4 + 2 \times 0.2) = 0.8.$$

Now, let us look at the case of using the quantifier "*as many as possible*." Then, we obtain, in order of preference, patterns #10, #14, and #18 as the top three. In this case, due to the requirement of meeting as many as possible of the five feeling targets $\{$*funny*, *pretty*, *flowery*, *bright*, *pale*$\}$, the aggregation operator $\mathcal{F}$ behaves toward an "AND" aggregation with the corresponding degree of "*andness*" (refer to (16) in Appendix I) being

$$\begin{aligned}\text{andness}(\mathcal{F}) &= 1 - \text{orness}(\mathcal{F})\\ &= 1 - \frac{1}{4}(2 \times 0.2 + 1 \times 0.4 + 0 \times 0.4)\\ &= 0.8.\end{aligned}$$

Then, pattern #10 in this case is still the most recommended one, having the highest aggregate value, which is the weighted sum of its three lowest degrees of target achievement for *funny*, *pretty*, and *pale*. Though it has a very bad score of 0.035 in meeting the *pale* target, its target achievements on *funny* and *pretty* are very good, making it the first recommended one. Pattern #14 in this case becomes the second recommended one having the second highest aggregate value of target achievement for *funny*, *flowery*, and *pale*, while having good scores in achieving *pretty* and *bright* targets. Looking at Fig. 10, one may have the impression that the uncertain judgments of patterns #14 and #18 on correspondingly selected features are somewhat similar. More concretely, pattern #18 has the third highest aggregate value of its three lowest degrees of target achievement also for *funny*, *flowery*, and *pale*, like the case of pattern #14, as shown in Table V.

Finally, if quantifier "*All*" is used, the aggregation operator $\mathcal{F}$ is a pure "AND" operator, i.e., andness$(\mathcal{F}) = 1$. In this case, we see that both patterns #10 and #14 disappear from the top three recommended items due to their target achievements of 0.035 and 0.121, respectively, for *pale*, while pattern #27 becomes the first recommended item, followed by patterns #30 and #29 that

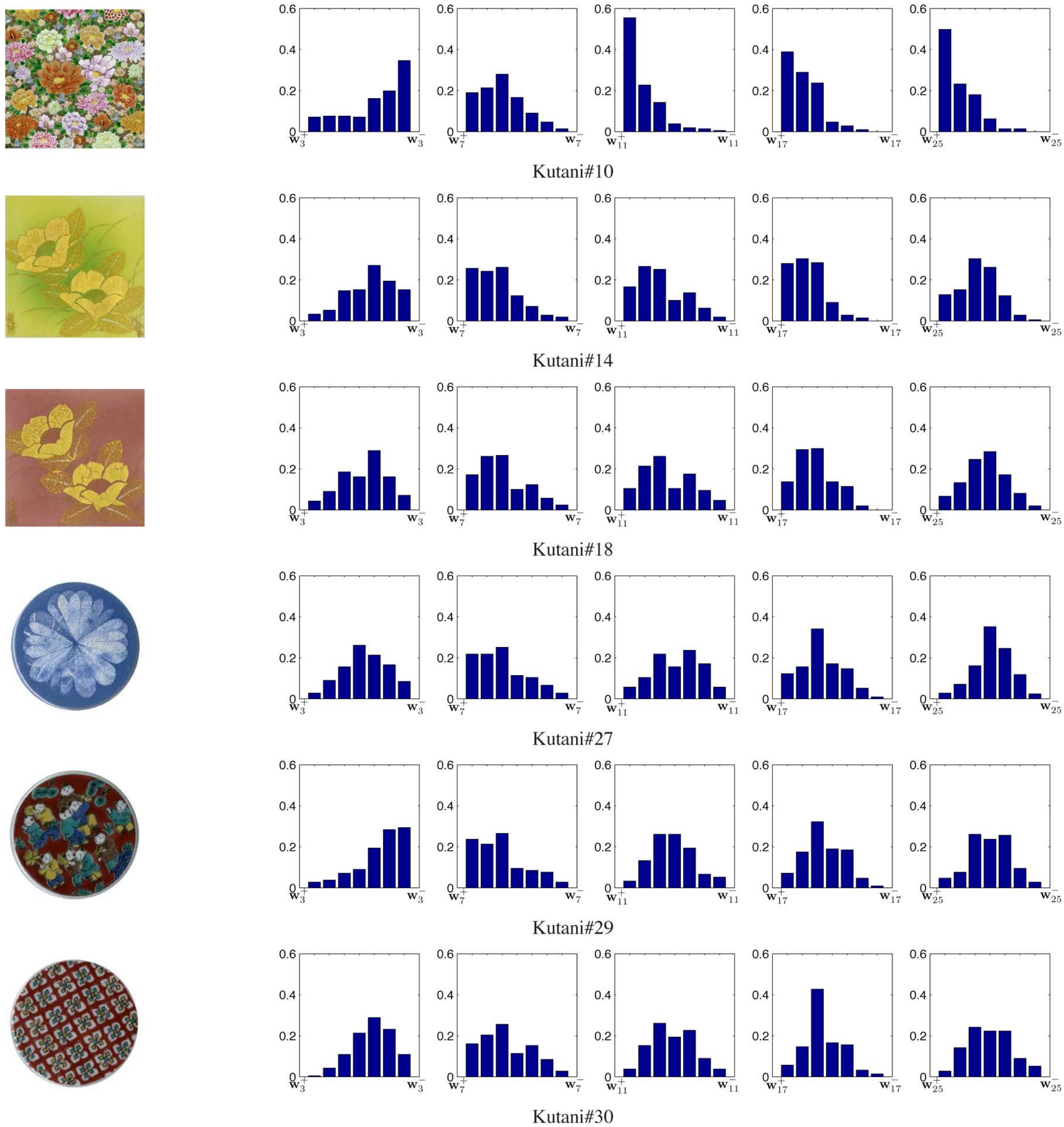

Fig. 10. Recommended patterns and those uncertain judgments for selected features.

TABLE V
TARGET ACHIEVEMENTS FOR SELECTED FEATURES OF RECOMMENDED PATTERNS

Patterns	Target Achievements					Aggregate Values			
	F_3	F_7	F_{11}	F_{17}	F_{25}	*Exists*	*ALH*	*AMAP*	*All*
#10	0.5353	0.4420	0.7461	0.6510	0.0351	**0.7461**	**0.6658**	**0.2979**	0.0351
#14	0.3903	0.5114	0.4325	0.5723	0.1210	**0.5723**	**0.5200**	**0.2910**	0.1210
#18	0.2995	0.4389	0.3454	0.4408	0.1830	0.4408	0.4210	**0.2621**	0.183
#27	0.3053	0.4565	0.2306	0.3647	0.2400	0.4565	0.3895	0.2493	**0.2306**
#29	0.5478	0.4732	0.2510	0.3228	0.2215	**0.5478**	**0.4730**	0.2535	**0.2215**
#30	0.3837	0.3955	0.2592	0.3211	0.2291	0.3955	0.3759	0.2595	**0.2291**

have the second and third highest aggregate values, respectively. We can observe that pattern #30 is clearly not very good at meeting any of the five feeling targets, as shown in Table V, it, however, is also not actually bad at target achievement for all five and, therefore, the purely AND aggregation associated with quantifier "*All*" would appropriately value it highly.

D. Comparative Study

The consumer-oriented evaluation model described before can be essentially viewed as a target-based multiattribute evaluation model, where each traditional craft item is evaluated in terms of its achievement on multiple feeling targets specified by a consumer. In order to ascertain the efficiency of this method, as well as to gain insight into how it works, we will conduct in this section a comparative study of the multiattribute evaluation method, making use of linguistic decision analysis with the 2-tuple linguistic representation model [13]. The main reason for using the 2-tuple-based evaluation approach is due to

$$F_k$$

$\mathbf{w}_k^+$	s_0	s_1	s_2	s_3	s_4	s_5	s_6	$\mathbf{w}_k^-$

Fig. 11. Linguistic values and their relation to a pair of kansei words.

its advantage over conventional fuzzy-set-based and symbolic approaches; it overcomes the limitations of the loss of information yielded by the process of linguistic approximation, and the lack of precision in final results inherently faced by these conventional approaches.

To make the 2-tuple linguistic representation model applicable to the evaluation problem at hand, we will treat qualitative assessments regarding each kansei feature given in the 7-point scale as linguistic assessments, accordingly taken from the set $\mathcal{S}$ of seven linguistic terms, as described in Fig. 11.

In the 2-tuple representation model, linguistic information is represented by a linguistic 2-tuple (s, α) composed of a linguistic term $s \in \mathcal{S}$ and a number $\alpha \in [-0.5, 0.5)$. The detailed definitions and 2-tuple aggregation operators are shown in Appendix II. Now, the evaluation method based on the 2-tuple representation model can be formulated as follows.

Given a request $[W, LQ]$ with $W = \{\mathbf{w}_{k_1}^*, \ldots, \mathbf{w}_{k_n}^*\}$ and LQ as a linguistic quantifier, let us decompose the set of indexes $I = \{k_1, \ldots, k_n\}$ into two disjoint subsets I^+ and I^- such that

$$I^+ = \{k_j \in I | \mathbf{w}_{k_j}^* = \mathbf{w}_{k_j}^+\} \qquad I^- = \{k_j \in I | \mathbf{w}_{k_j}^* = \mathbf{w}_{k_j}^-\}. \tag{9}$$

Then, for each object $o_i \in \mathcal{O}$, the performance of o_i on the kansei feature F_{k_j} is evaluated by

$$V_{k_j}(o_i) = \Delta\left(\sum_{s \in \mathcal{S}} f_{ik_j}(s)\Delta^{-1}(s, 0)\right), \qquad \text{if } k_j \in I^- \tag{10}$$

and

$$V_{k_j}(o_i) = \Delta\left(\sum_{s \in \mathcal{S}} f_{ik_j}(s)\Delta^{-1}(\mathrm{Neg}((s, 0)))\right), \quad \text{if } k_j \in I^+ \tag{11}$$

where $f_{ik_j}(s)$ is defined by

$$f_{ik_j}(s) = \frac{|\{S_h \in \mathcal{P} : x_{hk_j}(o_i) = s\}|}{|\mathcal{P}|} \tag{12}$$

i.e., $V_{k_j}(o_i)$ is the mean value of uncertain linguistic assessment of o_i regarding the kansei feature F_{k_j} computed by means of linguistic 2-tuples. Once values $V_{k_j}(o_i)$ have been computed for all features $F_{k_j}, k_j \in I$, the overall performance of o_i is calculated by aggregating all of them using an OWA operator $\mathcal{F}$ of dimension n similar to (8), such as

$$V(o_i) = \mathcal{F}(V_{k_1}(o_i), \ldots, V_{k_n}(o_i))$$

with the associated weighting vector $[w_1, \ldots, w_n]$ determined by using the fuzzy-set-based semantics of linguistic quantifier LQ.

Let us return to the consumer's request as considered before with

$$W = \{\mathbf{w}_3^-, \mathbf{w}_7^+, \mathbf{w}_{11}^+, \mathbf{w}_{17}^+, \mathbf{w}_{25}^-, \}.$$

TABLE VI
QUANTIFIERS USED AND CORRESPONDING TOP THREE ITEMS USING THE 2-TUPLE-BASED METHOD

Linguistic quantifier	Weighting vector	The top 3 patterns
As many as possible (AMAP)	$[0, 0, 0.2, 0.4, 0.4]$	#14 $\succeq$ #30 $\succeq$ #29
All	$[0, 0, 0, 0, 1]$	#29 $\succeq$ #30 $\succeq$ #27
There exists	$[1, 0, 0, 0, 0]$	#10 $\succeq$ #14 $\succeq$ #29
At least haft (ALH)	$[0.4, 0.4, 0.2, 0, 0]$	#10 $\succeq$ #14 $\succeq$ #03

Then, we have $I^+ = \{7, 11, 17\}$ and $I^- = \{3, 25\}$. Using the 2-tuple-based computational method just described, we obtain the results of the top three recommended items with different linguistic quantifiers applied, as shown in Table VI. Table VII shows the performance of these items regarding the selected kansei features and their aggregate values on which the rankings are based on.

As we have seen from Table VI, the result yielded by the 2-tuple-based method is quite different from that obtained by the target-based method, as shown in Table IV, except for the case of quantifier "*there exists*." Particularly, in the first case with quantifier "*as many as possible*," pattern #10 that was ranked first by the target-based method disappears from the top three recommended items, while pattern #14 becomes the first, followed by #30 and #29 as the second and the third, respectively. It is of interest to note here that, as mentioned previously, the uncertain judgments of patterns #14 and #18 on correspondingly selected features are somewhat similar. However, #18 that was ranked third by the target-based method drops out of the top three. A position interchange of patterns #27 and #29 happens when compared with the result by the target-based method for the case of quantifier "*All*." In the case of quantifier "*at least half*," pattern #03 becomes the third, instead of #29 that was recommended by the target-based method.

The difference in results of rankings between the two methods occurs because in the 2-tuple-based method, only preferences over the linguistic term set $\mathcal{S}$ induced from the consumer's request are taken into account, while the target-based method considers not only these preferences, but also feeling targets specified by the consumer. From a decision analysis point of view, after determining consumer-specified preferences, the 2-tuple-based method applies the expected value model [refer to (10) and (11)] to evaluate the performance of an object regarding each kansei feature specified by the consumer. Thus, as discussed by Huynh *et al*. [18], the 2-tuple-based method works similarly to the target-based method when the "neutral target" is used. In particularly, if we define targets as

$$\pi_{k_l}(v_h) = 1$$

instead of the targets defined in (3), then the result obtained by the target-based method is the same as that produced by the 2-tuple-based method. This means that the target-based method can provide recommendations that would interestingly reflect attitudes of consumers about feeling targets, whilst those recommended by the 2-tuple-based method would not do so.

TABLE VII
PERFORMANCE OF RECOMMENDED ITEMS FOR SELECTED FEATURES USING THE 2-TUPLE-BASED METHOD

Patterns	Performance					Aggregate Values			
	F_3	F_7	F_{11}	F_{17}	F_{25}	*Exists*	*ALH*	*AMAP*	*All*
#03	$(s_3, 0.46)$	$(s_4, 0.37)$	$(s_2, -0.02)$	$(s_4, 0.06)$	$(s_4, -0.3)$	$(s_4, 0.37)$	$(\mathbf{s_4}, \mathbf{0.111})$	$(s_3, -0.09)$	$(s_2, -0.02)$
#10	$(s_4, 0.16)$	$(s_4, 0.05)$	$(s_5, 0.20)$	$(s_5, -0.07)$	$(s_1, -0.1)$	$(\mathbf{s_5}, \mathbf{0.20})$	$(\mathbf{s_5}, \mathbf{-0.12})$	$(s_3, -0.19)$	$(s_1, -0.10)$
#14	$(s_4, -0.24)$	$(s_4, 0.33)$	$(s_4, -0.04)$	$(s_5, -0.33)$	$(s_2, 0.20)$	$(\mathbf{s_5}, \mathbf{-0.33})$	$(\mathbf{s_4}, \mathbf{0.39})$	$(\mathbf{s_3}, \mathbf{0.18})$	$(s_2, 0.20)$
#27	$(s_3, 0.38)$	$(s_4, 0.02)$	$(s_3, -0.15)$	$(s_4, -0.26)$	$(s_3, 0.16)$	$(s_4, 0.02)$	$(s_4, -0.22)$	$(s_3, 0.08)$	$(\mathbf{s_3}, \mathbf{-0.15})$
#29	$(s_4, 0.41)$	$(s_4, 0.08)$	$(s_3, 0.14)$	$(s_4, -0.42)$	$(s_3, -0.02)$	$(\mathbf{s_4}, \mathbf{0.41})$	$(s_4, 0.11)$	$(\mathbf{s_3}, \mathbf{0.16})$	$(\mathbf{s_3}, \mathbf{-0.02})$
#30	$(s_4, -0.13)$	$(s_4, -0.26)$	$(s_3, 0.16)$	$(s_4, -0.37)$	$(s_3, -0.05)$	$(s_4, -0.13)$	$(s_4, -0.23)$	$(\mathbf{s_3}, \mathbf{0.17})$	$(\mathbf{s_3}, \mathbf{-0.05})$

V. CONCLUDING REMARKS

In summary, in this paper, we have first formulated the evaluation problem of Japanese traditional crafts, in which product items are essentially evaluated according kansei features reflecting aesthetic aspects of human perception. As, in practice, decisions on which traditional items to purchase or use are heavily influenced by personal feelings/characteristics, we have proposed a consumer-oriented evaluation model that targets these requests specified by consumers' feeling preferences. Particularly, the proposed evaluation model aims at providing a recommendation to a particular consumer regarding which product items would best meet her feeling preferences predefined. A case study of evaluating Kutani porcelain patterns has also been conducted to illustrate the proposed evaluation model.

Note that the focus of this paper is on the evaluation of traditional craft products using kansei data, this evaluation would hopefully serve the purpose of highly individualized recommendations, rather than being used for the purpose of product design, on which most previous studies of Kansei engineering have focused. The main aim of many Kansei engineering studies is to develop the product prototypes that would generate specific consumer feelings. In these studies, discovering relationships between kansei data and design elements is essential, and plays a crucial role. For this task, traditionally, Kansei engineering methods utilized multivariate statistical analysis such as principle component analysis and regression analysis, which typically treat kansei data as numerical data, together with the assumption of the existence of linear relations between consumer affections and design elements. However, it is also argued that assessments of some kansei features may show nonlinear characteristics compared to the horizontal numerical change on design elements, and therefore, applying multivariate analysis to these kansei data might not be appropriate [2], [29]. Recently, it has been shown that rough set theory can be properly applied to analyze kansei data [33]–[35] in Kansei engineering, irrespective of linear or nonlinear characteristics, in which kansei data are conventionally treated as categorical data. However, despite the differences in techniques applied, the SD method is still the most commonly used instrument for gathering kansei data. As the evaluation purpose of the present paper is for personalized recommendations and not for product design, the evaluation process was not involved in the aforementionedmentioned relationships between consumer feelings and design elements, and the kansei data were treated symbolically similar as in the rough-set-based approach.

Typically, the proposed recommendation method aims to maximize the probability of a product meeting feeling targets specified by a particular consumer, in which preference relations over the SD scale toward either of the opposite kansei words are determined directly by the consumer's feeling targets. Although this approach is an appealing and intuitively natural approach to consumer-oriented evaluation making use of target-oriented decision analysis, some directions remain in which we must extend our proposed approach before hopefully bringing it into practical application. First, it is helpful not only in taking (qualitative) kansei features, but also quantitative features of traditional products, such as price and size, into consideration in the evaluation framework. Second, though we have taken uncertainty in assessments of kansei features into our formulation in the proposed evaluation method, by treating kansei data as categorical data, we may have possibly ignored the ambiguous characteristics inherent to human judgments regarding kansei features. This can be addressed with the help of fuzzy sets and fuzzy-set-based extension of target-oriented decision analysis developed recently in [19]. Finally, we want to apply the proposed method to an online store, and see how it would satisfy the needs of real consumers, so that possible improvements can be developed.

APPENDIX I

OWA OPERATORS AND LINGUISTIC QUANTIFIERS

The notion of OWA operators was first introduced in [43] regarding the problem of aggregating multicriteria to form an overall decision function. Since its invention by Yager in [43], OWA operator has been extensively studied, and has been found useful in many applications of information fusion and decision making (see, e.g., [45] and references therein). By definition, an OWA operator of dimension n is a mapping

$$\mathcal{F} : [0,1]^n \to [0,1]$$

associated with a weighting vector $w = [w_1, \ldots, w_n]$, such that: 1) $w_i \in [0,1]$ and 2) $\sum_i w_i = 1$, and

$$\mathcal{F}(a_1, \ldots, a_n) = \sum_{i=1}^{n} w_i b_i$$

TABLE VIII
LINGUISTIC QUANTIFIERS AND THE AGGREGATION BEHAVIOR OF CORRESPONDING $\mathcal{F}$

Linguistic quantifier	Membership function Q	Weighting vector	Aggregation behavior of $\mathcal{F}$
there exists	$Q(r) = \begin{cases} 0 & \text{if } r = 0 \\ 1 & \text{if } r > 0 \end{cases}$	$[1, 0, 0, 0, 0]$	$orness(\mathcal{F}) = 1$
for all	$Q(r) = \begin{cases} 1 & \text{if } r = 1 \\ 0 & \text{if } r \neq 1 \end{cases}$	$[0, 0, 0, 0, 1]$	$orness(\mathcal{F}) = 0$
identity	$Q(r) = r$	$[0.2, 0.2, 0.2, 0.2, 0.2]$	$orness(\mathcal{F}) = 0.5$
at least half	$Q(r) = \begin{cases} 2r & \text{if } 0 \leq r \leq 0.5 \\ 1 & \text{if } 0.5 \leq r \leq 1 \end{cases}$	$[0.4, 0.4, 0.2, 0, 0]$	$orness(\mathcal{F}) = 0.8$
as many as possible	$Q(r) = \begin{cases} 0 & \text{if } 0 \leq r \leq 0.5 \\ 2r - 1 & \text{if } 0.5 \leq r \leq 1 \end{cases}$	$[0, 0, 0.2, 0.4, 0.4]$	$orness(\mathcal{F}) = 0.2$
most	$Q(r) = \begin{cases} 0 & \text{if } 0 \leq r \leq 0.3 \\ 2r - 0.6 & \text{if } 0.3 \leq r \leq 0.8 \\ 1 & \text{if } 0.8 \leq r \leq 1 \end{cases}$	$[0, 0.2, 0.4, 0.4, 0]$	$orness(\mathcal{F}) = 0.45$

where b_i is the ith largest element in the vector $[a_1, \ldots, a_n]$ and $b_1 \geq b_2 \geq \cdots \geq b_n$. As such, the key step of this aggregation is reordering of arguments a_j in a descending order so that the weight w_i is associated with the ordered position of the argument, rather than associated with the argument itself.

OWA operators provide a type of aggregation operator between the "AND" and the "OR" aggregations. As suggested by Yager [43], there exist at least two methods for obtaining weights w_i's. The first approach is to use some kind of learning mechanism, i.e., we use some sample data, arguments, and associated aggregate values, and try to fit the weights to this collection of sample data. The second approach is to give some semantics or meaning to the weights. Then, based on these semantics, we can directly provide the values for the weights. For the purpose of this paper, let us introduce the semantics based on fuzzy linguistic quantifiers for the weights.

The fuzzy linguistic quantifiers were introduced by Zadeh in [50]. According to Zadeh, there are basically two types of quantifiers: absolute and relative. Here, we focus on the relative quantifiers typified by terms such as *most*, *at least half*, and *as many as possible*. A relative quantifier Q is defined as a mapping $Q : [0, 1] \to [0, 1]$ verifying $Q(0) = 0$, there exists $r \in [0, 1]$ such that $Q(r) = 1$, and Q is a nondecreasing function. For example, the membership function of relative quantifiers can be simply defined [12] as

$$Q(r) = \begin{cases} 0, & \text{if } r < a \\ \frac{r-a}{b-a}, & \text{if } a \leq r \leq b \\ 1, & \text{if } r > b \end{cases} \tag{13}$$

with parameters $a, b \in [0, 1]$.

Then, Yager [43] proposed to compute the weights w_i's based on the linguistic quantifier represented by Q as follows:

$$w_i = Q\left(\frac{i}{n}\right) - Q\left(\frac{i-1}{n}\right), \qquad \text{for } i = 1, \ldots, n. \tag{14}$$

In addition, the so-called measure "*orness*" of OWA operator $\mathcal{F}$ associated with weighting vector $w = [w_1, \ldots, w_n]$ is defined as

$$\text{orness}(\mathcal{F}) = \frac{1}{n-1} \sum_{i=1}^{n} ((n-i) \times w_i). \tag{15}$$

This measure of "*orness*" indicates to which degree the operator $\mathcal{F}$ behaves like an "OR" aggregation. Also, the measure of "*andness*" associated with $\mathcal{F}$ is defined as the complement of its "*orness*.," then

$$\text{andness}(\mathcal{F}) = 1 - \text{orness}(\mathcal{F}) \tag{16}$$

which indicates how much degree the operator $\mathcal{F}$ behaves like an "AND" aggregation.

Table VIII provides typical examples of linguistic quantifiers associated with their membership functions, all of which are taken from the literature [12], [43], and the aggregation behavior of corresponding OWA $\mathcal{F}$ for the case $n = 5$, which has been used for illustration in Section IV.

APPENDIX II

COMPUTATIONAL MODEL BASED ON LINGUISTIC 2-TUPLES

The 2-tuple linguistic representation model has been proposed by Herrera and Martínez [13] in order to provide an appropriate tool for computing with words, which aims at overcoming the limitation of the loss of information caused by the process of linguistic approximation in the conventional fuzzy-set-based and symbolic approaches.

A. 2-Tuple Representation of Linguistic Information

Let $\mathcal{S} = \{s_0, \ldots, s_g\}$ be a linguistic term set on which a total order is defined as: $s_i \leq s_j \Leftrightarrow i \leq j$. In addition, a negation operator Neg can be defined by: $\text{Neg}(s_i) = s_j$ such that $j = g - i$, where $g + 1$ is the cardinality of $\mathcal{S}$. In general, applying a symbolic method for aggregating linguistic information often yields a value $\beta \in [0, g]$ and $\beta \notin \{0, \ldots, g\}$, then a symbolic approximation must be used to get the result expressed in $\mathcal{S}$.

To avoid any approximation process that causes a loss of information in the processes of computing with words, alternatively, the 2-tuple linguistic representation model takes $\mathcal{S} \times [-0.5, 0.5)$ as the underlying space for representing information. In this representation space, if a value $\beta \in [0, g]$ represents the result of a linguistic aggregation operation, then the 2-tuple (s_i, α) that expresses the information equivalent to

β is obtained by means of the following transformation:

$$\Delta : [0, g] \longrightarrow \mathcal{S} \times [-0.5, 0.5)$$
$$\beta \longmapsto (s_i, \alpha)$$

with

$$\begin{cases} i = \mathrm{round}(\beta) \\ \alpha = \beta - i \end{cases}$$

and then, α is called a *symbolic translation*, which supports the "difference of information" between the value $\beta \in [0, g]$ obtained after a symbolic aggregation operation, and the closest value in $\{0, \ldots, g\}$ indicating the index of the best matched term in $\mathcal{S}$.

Inversely, a 2-tuple $(s_i, \alpha) \in \mathcal{S} \times [-0.5, 0.5)$ can also be equivalently represented by a numerical value in $[0, g]$ by means of the following transformation:

$$\Delta^{-1} : \mathcal{S} \times [-0.5, 0.5) \longrightarrow [0, g]$$
$$(s_i, \alpha) \longmapsto \Delta^{-1}(s_i, \alpha) = i + \alpha.$$

Under such transformations, it should be noted here that any original linguistic term s_i in S is then represented by its equivalent 2-tuple $(s_i, 0)$ in the 2-tuple linguistic model.

B. Comparison of Linguistic 2-Tuples and Negation

The comparison of linguistic information represented by 2-tuples is defined as follows. Let (s_i, α_1) and (s_j, α_2) be two 2-tuples, then the following holds.

1) if $i < j$, then (s_i, α_1) is less than (s_j, α_2).
2) if $i = j$, then
   a) if $\alpha_1 = \alpha_2$, then (s_i, α_1) and (s_j, α_2) represent the same information;
   b) if $\alpha_1 < \alpha_2$, then (s_i, α_1) is less than (s_j, α_2);
   c) if $\alpha_1 > \alpha_2$, then (s_i, α_1) is greater than (s_j, α_2).

Using two 2-tuple transformations defined before, the negation operator over 2-tuples is defined as follows:

$$\mathrm{Neg}((s_i, \alpha)) = \Delta(g - (\Delta^{-1}(s_i, \alpha))). \quad (17)$$

C. Aggregation of Linguistic 2-Tuples

Making use of 2-tuple transformations Δ and Δ^{-1}, linguistic information represented by 2-tuples can be transformed into numerical information and *vice versa* without loss of information. Therefore, many aggregation operators proposed in the literature for dealing with numerical information can be easily extended to work with linguistic 2-tuples [13].

Let $\mathbf{x} = [(r_1, \alpha_1), \ldots, (r_n, \alpha_n)]$ be a vector of linguistic 2-tuples, the 2-tuple arithmetic mean $\overline{\mathbf{x}}^e$ is computed as

$$\overline{\mathbf{x}}^e((r_1, \alpha_1), \ldots, (r_n, \alpha_n)) = \Delta\left(\sum_{i=1}^{n} \frac{1}{n} \Delta^{-1}(r_i, \alpha_i)\right). \quad (18)$$

When different 2-tuples $\mathbf{x}_i = (r_i, \alpha_i)$ have different numerical weights indicating their relative importance in the aggregation, the weighted average operator over 2-tuples is then defined as follows:

$$\overline{\mathbf{x}}^w((r_1, \alpha_1), \ldots, (r_n, \alpha_n)) = \Delta\left(\frac{\sum_{i=1}^{n} w_i \Delta^{-1}(r_i, \alpha_i)}{\sum_{i=1}^{n} w_i}\right) \quad (19)$$

where $\mathbf{w} = [w_1, \ldots, w_n]$ is the weighting vector associated with $\mathbf{x}$.

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