A Linguistic Decision Based Model Applied to Olive Oil Sensory Evaluation

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Abstract The evaluation is a process that analyzes elements to achieve different objectives such as quality inspection, design, marketing exploitation and other fields in industrial companies. In many of these fields the items, products, designs, etc., are evaluated according to the knowledge acquired via human senses (sight, taste, touch, smell and hearing), in such cases, the process is called *Sensory Evaluation*. In this type of evaluation process, an important problem arises as it is the modelling and management of uncertain knowledge, because the information acquired by our senses throughout human perceptions involves uncertainty, vagueness and imprecision. The Fuzzy Linguistic Approach [34] has showed its ability to deal with uncertainty, ambiguity, imprecision and vagueness, so it seems logic and suitable the use of the Fuzzy Linguistic Approach to model the information provided by the experts in sensory evaluation processes.

The decision analysis has been usually used in evaluation processes because it is a formal methodology that can help to achieve the evaluation objectives. In this chapter we present a linguistic evaluation model for sensory evaluation based on the decision analysis scheme that will use the Fuzzy Linguistic Approach and the 2-tuple fuzzy linguistic representation to model and manage the uncertainty and vagueness of the information acquired through the human perceptions in the sensory evaluation process. This model will be applied to some sensory evaluation processes of the Olive Oil.

1 Introduction

The evaluation is a complex cognitive process that involves different mechanisms in which it is necessary to define the elements to evaluate, fix the evaluation framework, gather the information and obtain an evaluation assessment by means of an evaluation process. The aim of any evaluation process is to obtain information about the worth of an item (product, service, material, etc.), a complete description about different aspects, indicators, criteria in order to improve it or to compare with other items to know which ones are the best. The information gathered in this kind of processes is usually provided by a group of individuals, called panel of experts, where

H. Bustince et al., (eds.), *Fuzzy Sets and Their Extensions: Representation, Aggregation and Models.*

each expert expresses their opinions about the item according to their knowledge and their own perceptions.

In this chapter our interest is focused on *Sensory Evaluation* processes[11, 29, 30] that is an evaluation discipline whose information, provided by a panel of experts, is perceived by the human senses of *sight, smell, taste, touch and hearing*. The sensory evaluation is widely used in:

- *Quality inspection* of food and textile products [1, 12, 13, 37] to determine systematically their characteristics by means of a group of experts.
- *Marketing studies* [22, 27] for understanding consumers behaviors and exploiting new markets.
- *Engineering processes* [7, 32] to integrate the data provided by the individuals in their design.
- Etc.

The sensory evaluation is based on the knowledge acquired in a sensory way by a panel of experts that take part in the evaluation process. A suitable mathematical formulation is not easy in this type of problems because human perceptions are subjective and not objective, therefore the assessments provided by the individuals are vague and uncertain. Initially classical computational techniques used in sensory evaluation were based on statistics and factorial analysis, but these methods are not efficient for solving sensory evaluation problems because uncertainties in this type of problems have a non-probabilistic character since they are related to imprecision and vagueness of meanings. In such a case, linguistic descriptors are direct provided by the experts to express their knowledge about the evaluated element. The Fuzzy Linguistic Approach [34] provides a systematic way to represent linguistic variables in an evaluation procedure. The use of linguistic variables implies processes of computing with words [20, 21, 33, 36] such as their fusion, aggregation, comparison, etc.

The evaluation process follows a methodology in order to achieve its objectives. The use of decision analysis approach has been successfully applied to evaluation problems in the literature [2, 8, 19, 25]. In decision theory before making a decision is carried out a decision analysis approach that allows people to make decisions more consistently, i.e., it helps people to deal with difficult decisions. The decision analysis is a suitable approach for evaluation processes because it helps to analyze the alternatives, aspects, indicators of the element/s under study that it is the objective of the evaluation processes. In the literature different linguistic decision making models can be found [6, 14, 24, 15].

The aim of this paper is to propose a linguistic sensory evaluation model based on a decision analysis scheme that uses the Fuzzy Linguistic Approach to represent the experts' assessments, and the 2-tuple fuzzy representation model [16] to provide a computational model to manage the processes of computing with words. And eventually to apply it to some sensory evaluation processes of the olive oil.

This paper is structured as follows, in Sect. 2 we present and review in short the necessary concepts and processes to develop the linguistic sensory evaluation. In Sect. 3 we present our proposal of linguistic sensory evaluation model, and in Sect. 4 we expound an application of this evaluation model. Finally, this paper is concluded in Sect. 5.

2 Preliminaries

Our evaluation model is based on the scheme of the Decision Analysis we shall present in this section. Moreover, we shall make a brief review of the Fuzzy Linguistic Approach and the Linguistic 2-tuple Representation Model that will be used to facilitate the computation of the lingusitic information in the evaluation process.

2.1 Decision Analysis Steps

The Decision Analysis is a discipline, which belongs to Decision Making Theory, whose purpose is to help the decision makers to reach a consistent decision in a decision making problem. The evaluation process can be modelled as different types of decision making problems.

In this chapter we model the evaluation process as a Multi-Expert Decision Making (MEDM) problem. In this type of decision problem, decision makers express their opinions about a set alternatives, in order to facilitate the selection of the best one(s). A classical decision analysis scheme is composed by the following phases (see Fig. 1):

- *Identify decision and objectives.*
- *Identify alternatives.*
- *Model:* For example, a decision problem is modelled as a MEDM [18] model that deals with a type of information.
- *Gathering information:* decision makers provide their information.
- *Rating alternatives:* This phase is also known as "aggregation phase" [28] due to the fact in this phase, the individual preferences are aggregated in order to obtain a collective value for each alternative.
- *Choosing best alternatives:* or "exploitation phase" [28] selects the solution from the set of alternatives applying a choice degree [3, 26] to the collective values computed in the previous phase.
- *Sensitive analysis:* in this step the information obtained is analyzed in order to know if it is good enough to make a decision, or otherwise, to go back to initial phases to improve the quantity or/and the quality of the information obtained.
- *Make a decision.*

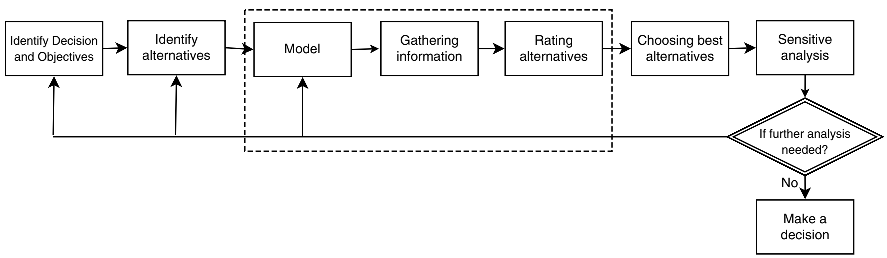

Fig. 1 Decision analysis scheme

The application of the decision analysis to an evaluation process does not imply the eight phases. The essential phases regarding an evaluation problem are dashed in a rectangle of the Fig. 1.

Additionally the use of *Linguistic* information adds two processes in the **model** and **rating** phases, such as:

1. *The choice of the syntax and semantics of the linguistic terms* that the experts will use to express their assessments about an evaluated element.
2. *To select a linguistic computational technique for rating alternatives* in order to deal with the assessments provided by the experts.

These processes are fixed regarding our proposal in the next subsections.

2.2 Fuzzy Linguistic Approach

Although we usually work in quantitative settings where the information is expressed by numerical values, sometimes we shall need to describe activities of the real world that cannot be assessed in a quantitative form, but rather in a qualitative one, i.e., with vague or imprecise knowledge. In that case, a better approach may be to use linguistic assessments instead of numerical values. The variables which participate in these problems are assessed by means of linguistic terms [34]. This approach is adequate in situations where the information may be unquantifiable due to its nature, and thus, it may be stated only in linguistic terms (e.g., when evaluating the “comfort” or “design” of a car, terms like “bad”, “poor”, “tolerable”, “average”, “good” can be used [23]. For instance, when attempting to qualify phenomena related to human perception, such as in sensory evaluation, we are often led to use words in natural language.

Even though, the linguistic approach is less precise than the numerical one, it provides some advantages as, the linguistic assessments are better understood by human beings than numerical ones or that with this approach we also diminished the effects of noise since, as it is known the more refined assessment scale is, the more sensitive to noise and consequently the more error facedown it becomes.

In short, the linguistic approach is appropriated for many problems, since it allows a more direct and adequate representation when we are unable to express it with precision. Hence, the burden of qualifying a qualitative concept is eliminated.

The fuzzy linguistic approach represents qualitative aspects as linguistic values by means of linguistic variables:

Definition 1. [34]. *A linguistic variable is characterized by a quintuple (H,T(H),U, G,M) in which H is the name of the variable; T(H) (or simply T) denotes the term set of H, i.e., the set of names of linguistic values of H, with each value being a fuzzy variable denoted generically by X and ranging across a universe of discourse U which is associated with the base variable u; G is a syntactic rule (which usually takes the form of a grammar) for generating the names of values of H; and M is a semantic rule for associating its meaning with each H,* $M(X)$*, which is a fuzzy subset of U.*

We have to choose the appropriate linguistic descriptors for the term set and their semantics. In order to accomplish this objective, an important aspect to analyze is the "*granularity of uncertainty*", i.e., the level of discrimination among different counts of uncertainty. The universe of the discourse over which the term set is defined can be arbitrary, in this paper we shall use linguistic term sets in the interval [0, 1]. In [4] the use of term sets with an odd cardinal was studied, representing the mid term by an assessment of "approximately 0.5", with the rest of the terms being placed symmetrically around it and with typical values of cardinality , such as 7 or 9.

One possibility of generating the linguistic term set consists of directly supplying the term set by considering all terms distributed on scale on which total order is defined [34]. For example, a set of seven terms S, could be given as follows:

$$S = \{s_0 : none, s_1 : verylow, s_2 : low, s_3 : medium, s_4 : high, s_5 : veryhigh,\\ s_6 : perfect\}$$

Usually, in these cases, it is required that in the linguistic term set there exist:

1. A negation operator $\text{Neg}(s_i) = s_j$ such that $j = g$-i (g+1 is the cardinality).
2. A max operator: $\max(s_i, s_j) = s_i \; if \; s_i \geq s_j$.
3. A min operator: $\min(s_i, s_j) = s_i \; if \; s_i \leq s_j$

The semantics of the terms is given by fuzzy numbers. A computationally efficient way to characterize a fuzzy number is to use a representation based on parameters of its membership function [4]. The linguistic assessments given by the users are just approximate ones, some authors consider that linear trapezoidal membership functions are good enough to capture the vagueness of those linguistic assessments. The parametric representation is achieved by the 4-tuple (a, b, d, c), where b and d indicate the interval in which the membership value is 1, with a and c indicating the left and right limits of the definition domain of the trapezoidal membership function [4]. A particular case of this type of representation are the linguistic assessments whose membership functions are triangular, i.e., $b = d$, then we represent this type of membership functions by a 3-tuple (a, b, c). An example may be the following:

$$\begin{array}{llll} P = (.83, 1, 1) & VH = (.67, .83, 1) & H = (.5, .67, .83) & M = (.33, .5, .67) \\ L = (.17, .33, .5) & VL = (0, .17, .33) & N = (0, 0, .17), & \end{array}$$

which is graphically showed in Fig. 2.

The use of linguistic variables implies processes of computing with words such as their fusion, aggregation, comparison, etc. To perform these computations there are different models in the literature:

- *The linguistic computational model based on the Extension Principle*, which allow us to aggregate and compare linguistic terms through computations on the associated membership functions [8].
- *The symbolic method* [10]. This symbolic model makes direct computations on labels, using the ordinal structure of the linguistic term sets.
- *The 2-tuple fuzzy linguistic computational model* [16]. It uses the 2-tuple fuzzy linguistic representation model and its characteristics to make linguistic computations, obtaining as results linguistic 2-tuples. A linguistic 2-tuple is defined by

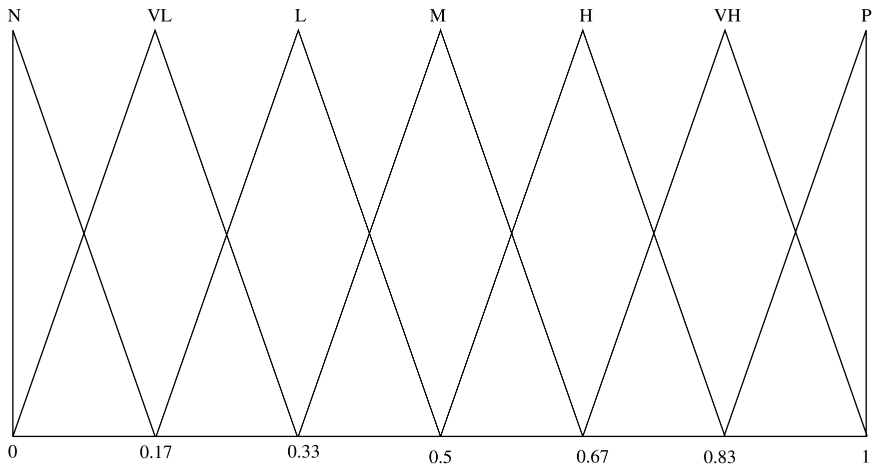

Fig. 2 A set of seven terms with its semantic

a pair of values, where the first one is a linguistic label and the second one is a real number that represents the value of the symbolic translation.

In the following subsection we shall review the 2-tuple model due to the fact, that it will be the computational model used in our evaluation process.

2.3 The 2-Tuple Fuzzy Linguistic Representation Model

This model has been presented in [16] and has showed itself as useful to deal with evaluation problems similar to the one we are facing in this paper [18, 18].

This linguistic model takes as basis the symbolic aggregation model [10] and in addition defines the concept of Symbolic Translation and uses it to represent the linguistic information by means of a pair of values called linguistic 2-tuple, (s, α), where s is a linguistic term and α is a numeric value representing the symbolic translation.

Definition 2. *Let β be the result of an aggregation of the indexes of a set of labels assessed in a linguistic term set $S = \{s_0, ..., s_g\}$, i.e., the result of a symbolic aggregation operation. $\beta \in [0, g]$, being $g + 1$ the cardinality of S. Let $i = round(\beta)$ and $\alpha = \beta - i$ be two values, such that, $i \in [0, g]$ and $\alpha \in [-.5, .5)$ then α is called a Symbolic Translation.*

Definition 3. [16] *Let $S = \{s_0, ..., s_g\}$ be a linguistic term set and $\beta \in [0, g]$ a value supporting the result of a symbolic aggregation operation, then the 2-tuple that expresses the equivalent information to β is obtained with the following function:*

$$\Delta : [0, g] \longrightarrow S \times [-0.5, 0.5)$$

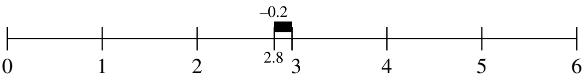

Fig. 3 Example of symbolic translation

$$\Delta(\beta) = \begin{cases} s_i & i = round(\beta) \\ \alpha = \beta - i & \alpha \in [-.5, .5) \end{cases} \tag{1}$$

where round is the usual round *operation,* s_i *has the closest index label to "*β*" and "*α*" is the value of the symbolic translation.*

Example 1. Let's suppose a symbolic aggregation operation over labels assessed in $S = \{s_0, s_1, s_2, s_3, s_4, s_5, s_6\}$ that obtains a result of $\beta = 2.8$, then the representation of this information by means of a 2-tuple will be:

$$\Delta\,(2.8) = (s_3, -0.2)$$

Graphically, it is represented in Fig. 3.

Proposition 1. [16] *Let* $S = \{s_0, ..., s_g\}$ *be a linguistic term set and* (s_i, α) *be a 2-tuple. There is a* Δ^{-1} *function, such that, from a 2-tuple it returns its equivalent numerical value* $\beta \in [0, g] \subset \mathcal{R}$*.*

Proof.

It is trivial, we consider the following function:

$$\Delta^{-1} : S \times [-.5, .5) \longrightarrow [0, g] \tag{2}$$
$$\Delta^{-1}(s_i, \alpha) = i + \alpha = \beta$$

Remark 1: From definitions 2 and 3 and from proposition 1, it is obvious that the conversion of a linguistic term into a linguistic 2-tuple consist of adding a value 0 as symbolic translation:

$$s_i \in S \Longrightarrow (s_i, 0)$$

This representation model has associated a computational model that was presented in [16]:

1. **Aggregation of 2-tuples:** The aggregation of linguistic 2-tuples consists of obtaining a value that summarizes a set of values, therefore, the result of the aggregation of a set of 2-tuples must be a linguistic 2-tuple. In [16] we can find several 2-tuple aggregation operators based on classical ones. Here we review the 2-tuple arithmetic mean and the 2-tuple weighted average operators, because we shall use them in our evaluation model:

   Definition 4. *Let* $x = \{(r_1, \alpha_1), \cdots, (r_n, \alpha_n)\}$ *be a set of 2-tuples, the extended Arithmetic Mean* AM^* *using the linguistic 2-tuples is computed as,*

$$AM^{*}\left((r_1,\alpha_1),\ldots,(r_n,\alpha_n)\right)=\Delta\left(\sum_{i=1}^{n}\frac{1}{n}\Delta^{-1}(r_i,\alpha_i)\right)=\Delta\left(\frac{1}{n}\sum_{i=1}^{n}\beta_i\right) \quad (3)$$

Example 2. Let $S = \{s_0, s_1, s_2, s_3, s_4, s_5, s_6\}$ a linguistic term set and $x = \{(s_2, 0.3), (s_5, -0.2), (s_3, 0)\}$ the set of 2-tuples we shall aggregate. The 2-tuple obtained after applying AM^* is:

$$AM^{*}\left((s_2,0.3),(s_5,-0.2),(s_3,0)\right)=\Delta\left(\frac{1}{3}\sum_{i=1}^{3}\Delta^{-1}(r_i,\alpha_i)\right)=$$
$$=\Delta\left(\frac{1}{3}(2.3+4.8+3)\right)=\Delta\left(\frac{1}{3}\cdot 10.1\right)=\Delta(3.36)=(s_3,0.36)$$

Definition 5. *Let $x = \{(r_1, \alpha_1), \cdots, (r_n, \alpha_n)\}$ be a set of 2-tuples and $W = \{w_1, \cdots, w_n\}$ its associated weights. The 2-tuples weighted mean, W_AM^*, is computed as:*

$$W\_AM^{*}\left((r_1,\alpha_1),\ldots,(r_n,\alpha_n)\right)=\Delta\left(\frac{\sum_{i=1}^{n}\Delta^{-1}(r_i,\alpha_i)\cdot w_i}{\sum_{i=1}^{n}w_i}\right)= \quad (4)$$
$$=\Delta\left(\frac{\sum_{i=1}^{n}\beta_i\cdot w_i}{\sum_{i=1}^{n}w_i}\right)$$

Example 3. Let $S = \{s_0, s_1, s_2, s_3, s_4, s_5, s_6\}$ a linguistic term set, $x = \{(s_2, 0.3), (s_5, -0.2), (s_3, 0)\}$ the set of 2-tuples we shall aggregate and $w = \{.0.2, 0.3, 0.5\}$ the associated weights. The 2-tuple obtained after applying W_AM^* is:

$$W\_AM^{*}\left((s_2,0.3),(s_5,-0.2),(s_3,0)\right)=\Delta\left(\frac{\sum_{i=1}^{3}\Delta^{-1}(r_i,\alpha_i)\cdot w_i}{\sum_{i=1}^{3}w_i}\right)=$$
$$\Delta\left(\frac{2.3\cdot 0.2+4.8\cdot 0.3+3\cdot 0.5}{0.2+0.3+0.5}\right)=\Delta(3.4)=(s_3,0.4)$$

More linguistic 2-tuple aggregation operators were defined in [16].

2. **Comparison of 2-tuples:** The comparison of information represented by 2-tuples is carried out according to an ordinary lexico-graphic order.
   - if $k < l$ then (s_k, α_1) is smaller than (s_l, α_2)
   - if $k = l$ then
     a) if $\alpha_1 = \alpha_2$ then (s_k, α_1), (s_l, α_2) represents the same information
     b) if $\alpha_1 < \alpha_2$ then (s_k, α_1) is smaller than (s_l, α_2)
     c) if $\alpha_1 > \alpha_2$ then (s_k, α_1) is bigger than (s_l, α_2)
3. **Negation Operator of a 2-tuple:** The negation operator over 2-tuples is defined as:

$$Neg\left(s_i, \alpha\right) = \Delta\left(g - \Delta^{-1}\left(s_i, \alpha\right)\right) \tag{5}$$

here $g + 1$ is the cardinality of S, $s_i \in S = \{s_0, \ldots, s_g\}$.

3 Linguistic Sensory Evaluation Model Based on Decision Analysis

We must keep in mind that the evaluation is used to measure, analyze and interpret the characteristics of the evaluated items according to the knowledge provided by a panel of experts. Classical evaluation methods need to define and know these requirements in an accurate way. However, in sensory evaluation problems the information provided by the experts has been perceived by the senses of sight, touch, smell, taste and hearing, and therefore, those requirements are subjective and involves uncertainty, vagueness and imprecision.

Our aim is to propose a Sensory Evaluation model based on the linguistic decision analysis whose mathematical formalism will be the linguistic 2-tuple model that improves the modelling of the uncertain information provided by the experts and improves the mathematical formalism to operate with this type of information in order to obtain accurate and reliable evaluation results. This proposal consists of the following evaluation phases that are graphically showed in Fig. 4.

- *Identify Evaluated Objects*. This phase is not formalized in this chapter because it is problem-dependent and each problem identifies its objects of interest.
- *Model:* this phase defines the evaluation framework that establishes the evaluation context in which the information is assessed and the problem solved.
- *Gathering information:* the experts express their sensory knowledge about the objects by means of linguistic assessments.
- *Rating objects:* we propose to use the 2-tuple computational model to obtain a rate for every object. In order to accomplish this step, suitable aggregation operators must be chosen.
- *Evaluation results:* it consists of analyzing the results obtained in the previous phase with the purpose of achieving the evaluation process. These results can be used in different ways, such as:

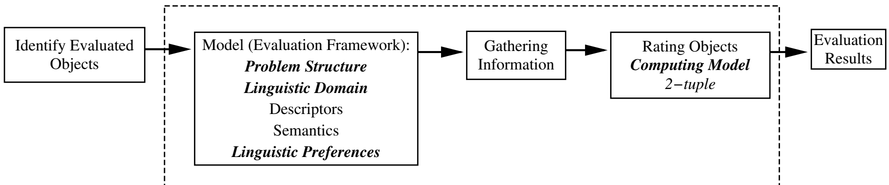

Fig. 4 A linguistic sensory evaluation scheme based on decision analysis

- To learn which element is better considered by the experts.
- To obtain a global value of an object that can be rated in a product scale to know its quality within its area.
- To know which features are better in the evaluated element.
- To compare several elements to study which aspects make better one element than another.
- To identify which aspects of an element should be improve in order to enhance its quality.
- Etc.

In the following subsections we shall present in further detail the main phases of our sensory evaluation model.

3.1 Model

This phase models the evaluation problem defining its evaluation framework, such that, the problem structure is defined and the linguistic descriptors and semantics that will be used by the experts to provide the information about the sensory features of the evaluated objects are chosen.

First of all, we must analyze which sensory features will be evaluated that depend on the evaluated object and which linguistic term set will be used to assess those features. The linguistic term set will be chosen according to:

1. *The accuracy of the evaluations:* since our senses could recognize and assess some features better than others, the granularity of the linguistic term set that describe those features must be chosen according to the accuracy of our perceptions.
2. *The experience of the experts:* Some of the senses need to be trained and, besides, they usually evolve as much as we used them. Therefore,the granularity of the linguistic term set used by an expert should be also chosen according to the expert's experience.

In this chapter we deal with an evaluation framework such that the different experts provide their sensory perceptions about item features by means of a linguistic label assessed in a fixed term set according to the above conditions. In such a case all the experts provide their sensory subjective preferences using one linguistic term set.

$E = \{e_1, ..., e_n\}$, group of experts
$S = \{s_0, ..., s_g\}$, linguistic term set
e_i expresses his/her preferences in S
over a group of sensory features $F = \{f_1, ..., f_h\}$
for a set of items, $X = \{x_1, ..., x_m\}$.

This context facilitates the computational processes of the evaluation problem because it is easy to define for the experts.

3.2 Gathering information

Due to the fact that the linguistic decision analysis used in this paper is based on the MEDM problems the experts provide their knowledge by means of utility vectors that contain a linguistic assessment for each evaluated feature.

$\{e_1, ..., e_n\}$, group of experts

$O = \{o_1, ..., o_m\}$, set of evaluated objects

$F = \{f_1, ..., f_h\}$, set of evaluated features for each object

$S = \{s_0, ..., s_g\}$, Linguistic term set

e_i provides his/her preferences in S by means of a utility vector:

$$U_i = \{u^i_{11}, ..., u^i_{1h}, u^i_{21}, ..., u^i_{2h}, ..., u^i_{m1}, ..., u^i_{mh}\}$$

where $u^i_{jk} \in S$ is the assessment provided to the feature f_k of the object o_j by the expert e_i.

Consequently in the gathering process every expert e_i will provide his/her utility vector U_i expressed by linguistic labels in the linguistic term set S fixed in the evaluation framework. Due to the fact that the evaluation model will use the linguistic 2-tuple computational model, the linguistic preferences provided by the experts will be transformed into linguistic 2-tuples according to the *Remark 1*.

3.3 Rating objects

In this phase the linguistic utility vectors provided by the experts and transformed into linguistic 2-tuples will be used in processes of Computing with Words in order to rate each evaluated object. To do so, the information gathered will be aggregated. Depending on the evaluation problem can be used different types of aggregation operators:

1. *Linguistic Aggregation operators of Non-Weighted information*. These operators aggregate the linguistic information provided by different sources with equal importance, i.e., all sources are equally important in the aggregation process. Examples of linguistic aggregation operators of non-weighted information can be found in [10, 31].
2. *Linguistic Aggregation operators of Weighted information*. These operators aggregate the information provided by different sources which are not equally important. Different proposals of this type of operators have been proposed in [5, 34].

Keeping in mind that the aim of this proposal is the use of a consistent mathematical formalism, as it is the linguistic 2-tuple computational model, to operate with the uncertain information provided by the experts it must be remarked that several aggregation operators of both types have been introduced for this linguistic computational model [16].

The rating process of this proposal consists of two steps:

1. *Computing collective evaluations for each feature*: in the gathering process each expert, e_i provides his/her preferences for every feature f_k of the object o_j by means of a utility assessment, u^i_{jk}. Then, the rating process in first place will compute a collective value for each feature, u_{jk}, using an aggregation operator, AG, on the assessments provided by the experts:

$$u_{jk} = AG(u^1_{jk}, ..., u^n_{jk}) \tag{6}$$

2. *Computing a collective evaluation for each object*: the final aim of the rating process is to obtain a global evaluation, u_j, of each evaluated object according to all the experts and features that take part in the evaluation process. To do so, this process will aggregate the collective features values u_{jk} for each object, o_j:

$$u_j = AG(u_{j1}, ..., u_{jh}) \tag{7}$$

The aggregation operators will depend on each evaluation problem taking into account if all experts or features are equally important or there are experts or features more important than the others.

The collective evaluation obtained will be the score obtained by the evaluated object in the sensory evaluation problem.

4 Evaluating Different Samples of Olive Oil to Obtain a Particular Flavor

Nowadays, the quality of the olive oil plays a key role in its production and final price. This quality depends on several aspects such as the condition of olives when enter the factory, the extraction processes and their sedimentation, or their storage.

The evaluation of the quality of the olive oil is not an easy task and is usually accomplished by Olive Oil Tasting Panel, in which there are between 8 and 12 connoisseurs, which will evaluate, by means of their perceptions acquired via their senses, the features that describe the samples of Olive Oil.

The combination of smell and taste is known as flavor and defines the organoleptic properties of the olive oil. So, we could talk about an olive oil with apple scent and sweet taste or an olive oil slightly pungent with almond scent.

These organoleptic properties, with acidity grade of the olive oil, are essential to obtain their quality. The acidity grade measures the level of free fatty acid, and therefore, an olive oil with a high acidity grade has more free fatty acid and is less healthy than an olive oil with a low acidity grade. Both aspects, the organoleptic properties and the acidity grade, establish the quality of the olive oil.

While it is easy to obtain the acidity grade of a sample of olive oil by means of chemical processes, the organoleptic properties need to be evaluated by the Tasting Panel that will use their perceptions to catch different aspects of its flavor such as fruity, bitter, pungent, etc. Besides, we must realize that although the most usual way utilized to express these perceptions is by means of numerical values, it is not the most suitable because this information has been acquired by means of perceptions, which usually involves uncertainty, vagueness and imprecision. In *http://www.oliveoilsource.com/tasteform1.pdf* we can find an example of a tasting sheet used by the panels of experts.

The companies in the olive oil market usually need to keep the flavor of their olive oil brands through time because its flavor is an essential characteristic of the brands. However, because it is impossible to obtain the quantity of the same kind of olives for the total production of an olive oil brand, they have to mix batches of olive oil in order to reproduce the same flavor. In these processes, the sensory evaluation plays a critical role because before starting any mixing process they need to know which batch of olive oil is suitable for being mixed, which organoleptic properties need to be improved or which ones need to be diminished. In these example, we shall show an example of how to evaluate four samples of olive oil, in order to find out the values of the organoleptic properties of sweetness and pungency. These values will be used in order to decide which batches should be mixed to obtain the flavor that the company is looking for.

Evaluation Framework

An Olive Oil Tasting Panel of eight connoisseurs $E = \{e_1, ..., e_8\}$ will evaluate the sensory feature *sweetness* of four samples of Olive Oil $O = \{o_1, ..., o_4\}$ and two sensory features $F = \{sweetness, pungency\}$. The panel will evaluate these sensory features independently in order to know the value of these features. To do so, two linguistic term set S and S' of nine terms and seven terms respectively were chosen according to conditions presented in subsection 3.1 to assess the sweetness and pungency respectively. Their syntax and semantics are the following ones (see Figs. 5 and 6).

$s_8 = Very\ sweet = (.88, 1, 1)$ $s_7 = Rather\ sweet = (.75, .88, 1)$
$s_6 = Sweet = (.62, .75, .88)$ $s_5 = A\ bit\ sweet = (.5, .62, .75)$
$s_4 = Average = (.38, .5, .62)$ $s_3 = A\ bit\ bitter = (.25, .38, .5)$
$s_2 = Bitter = (.12, .25, .38)$ $s_1 = Rather\ bitter = (0, .12, .25)$
$s_0 = Very\ bitter = (0, 0, .12)$

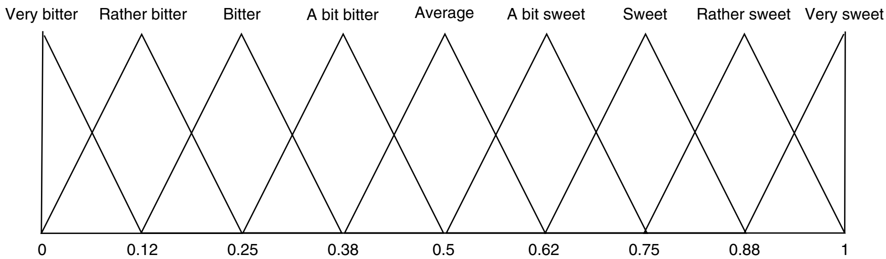

Fig. 5 A set of nine terms with its semantic chosen to evaluate the *sweetness*

$s'_6 = Very\ pungent = (.83, 1, 1)$ $s'_5 = Pungent = (.66, .83, .1)$
$s'_4 = A\ bit\ pungent = (.5, .66, .83)$ $s'_3 = Average = (.33, .5, .66)$
$s'_2 = A\ bit\ bland = (.17, .33, .5)$ $s'_1 = Bland = (.0, .17, .33)$
$s'_0 = Very\ bland = (0, 0, .17)$

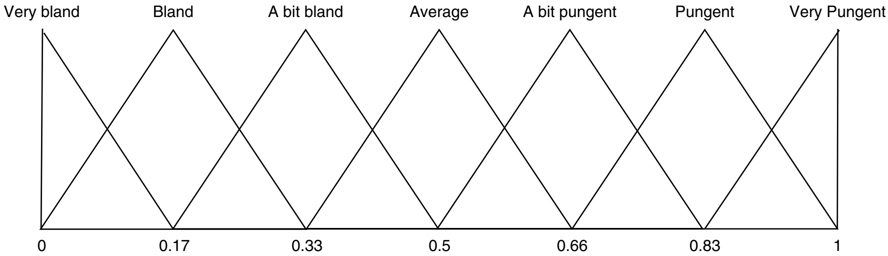

Fig. 6 A set of nine terms with its semantic chosen to evaluate the *pungency*

Gathering Process

The preferences of our Tasting Panel for sweetness and pungency are showed in Table 1 and Table 2 respectively.

Now, we shall transform their preferences into 2-tuple representation model (Table 3 and Table 4) to manage easily this information.

Rating Objects

In this phase we shall carry out the following steps:

Table 1 Olive Oil Tasting Panel's utility vectors for the feature *sweetness*

	e_1	e_2	e_3	e_4	e_5	e_6	e_7	e_8
o_1	s_4	s_2	s_5	s_3	s_4	s_5	s_2	s_7
o_2	s_4	s_3	s_4	s_2	s_2	s_4	s_5	s_3
o_3	s_3	s_3	s_5	s_4	s_3	s_2	s_4	s_2
o_4	s_5	s_4	s_4	s_5	s_6	s_3	s_7	s_3

Table 2 Olive Oil Tasting Panel's utility vectors for the feature *pungency*

	e_1	e_2	e_3	e_4	e_5	e_6	e_7	e_8
o_1	s'_4	s'_3	s'_4	s'_5	s'_6	s'_4	s'_4	s'_7
o_2	s'_5	s'_5	s'_6	s'_3	s'_1	s'_2	s'_5	s'_2
o_3	s'_3	s'_4	s'_5	s'_3	s'_2	s'_3	s'_3	s'_3
o_4	s'_4	s'_3	s'_5	s'_4	s'_5	s'_4	s'_7	s'_2

Table 3 Olive Oil Tasting Panel's utility vectors for the feature *sweetness* over the 2-tuple representation model

	e_1	e_2	e_3	e_4	e_5	e_6	e_7	e_8
o_1	$(s_3, 0)$	$(s_3, 0)$	$(s_6, 0)$	$(s_4, 0)$	$(s_6, 0)$	$(s_6, 0)$	$(s_4, 0)$	$(s_7, 0)$
o_2	$(s_4, 0)$	$(s_3, 0)$	$(s_4, 0)$	$(s_2, 0)$	$(s_2, 0)$	$(s_4, 0)$	$(s_5, 0)$	$(s_3, 0)$
o_3	$(s_3, 0)$	$(s_3, 0)$	$(s_5, 0)$	$(s_4, 0)$	$(s_3, 0)$	$(s_3, 0)$	$(s_4, 0)$	$(s_2, 0)$
o_4	$(s_4, 0)$	$(s_3, 0)$	$(s_4, 0)$	$(s_4, 0)$	$(s_5, 0)$	$(s_3, 0)$	$(s_7, 0)$	$(s_3, 0)$

Table 4 Olive Oil Tasting Panel's utility vectors for the feature *pungency* over the 2-tuple representation model

	e_1	e_2	e_3	e_4	e_5	e_6	e_7	e_8
o_1	$(s'_4, 0)$	$(s'_3, 0)$	$(s'_4, 0)$	$(s'_5, 0)$	$(s'_6, 0)$	$(s'_4, 0)$	$(s'_4, 0)$	$(s'_7, 0)$
o_2	$(s'_5, 0)$	$(s'_5, 0)$	$(s'_6, 0)$	$(s'_3, 0)$	$(s'_1, 0)$	$(s'_2, 0)$	$(s'_5, 0)$	$(s'_2, 0)$
o_3	$(s'_3, 0)$	$(s'_4, 0)$	$(s'_5, 0)$	$(s'_3, 0)$	$(s'_2, 0)$	$(s'_3, 0)$	$(s'_3, 0)$	$(s'_3, 0)$
o_4	$(s'_4, 0)$	$(s'_3, 0)$	$(s'_5, 0)$	$(s'_4, 0)$	$(s'_5, 0)$	$(s'_4, 0)$	$(s'_7, 0)$	$(s'_2, 0)$

1. *Computing collective values for each feature:* In order to simplify the example we have considered that all the experts are equally important. Therefore, we have used the arithmetic mean for 2-tuples for aggregating the information provided by the experts (Tables 5 and 6) obtaining a collective value for sweetness and pungency for each sample according to all the connoisseurs:
2. *Computing a collective evaluation for each object:* In this example the objective is to obtain the evaluation of different organoleptic features independently of each other to classify the different olive oil batches. So it is not necessary to obtain a global evaluation of each olive batch according to the two properties analyzed. However it is important to point out that if it would be necessary to obtain this global evaluation value we should use an aggregation method able to manage linguistic information assessed in different linguistic term sets as the methods showed in [18, 18].

Evaluation Results

The purpose of this evaluation process was to find out the values of different samples of olive oil regarding their sweetness and pungency properties . If we analyze the aforesaid results (Tables 5 and 6), the sample o_1 obtains the highest score for both

Table 5 Olive Oil Tasting Panel's collective utility vector for the *sweetness*

o_1	o_2	o_3	o_4
$(s_5 = A\ b\ sw, -.125)$	$(s_3 = A\ b\ bit, .375)$	$(s_3 = A\ b\ bit, .375)$	$(s_4 = Av, .25)$

Table 6 Olive Oil Tasting Panel's collective utility vector for the *pungency*

o_1	o_2	o_3	o_4
$(s'_5 = Pungent, -.375)$	$(s'_4 = A\ b\ Pun, -.375)$	$(s'_3 = Av, .25)$	$(s'_4 = A\ b\ Pun., .25)$

features. The first one, the sweetness, is assessed with *A bit sweet* and therefore it is above the average. The second one, its pungency, is *Pungent* and it is above the average as well.

5 Concluding Remarks

When we face a sensory evaluation problem we must realize that we are going to work with knowledge that has been acquired via the human senses sight, taste, touch, smell and hearing. This knowledge is better expressed using words instead of numbers, because humans cannot measure exactly with their senses and words gather accurately the uncertainty related to this way of acquisition of knowledge.

In this paper, we have proposed a sensory evaluation model based on the linguistic decision analysis since it has been applied successfully to similar evaluation problems and we have used the 2-tuple computational model in order to exploit the information because of the advantages that 2-tuple model offers regarding other linguistic computational models.

Finally we have showed an example of how to apply this model to a specific sensory evaluation problem, the evaluation of virgin olive oil, in order to expose the advantages of its use.

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References

1. A.M. Allison and T. Work. Fiery and frosty foods pose challenges in sensory evaluation. *Food Technology*, 58(5):32–37, 2004.
2. J. Antes, L. Campen, U. Derigs, C Titze, and G.D. Wolle. A model-based decision support system for the evaluation of flight schedules for cargo airlines. *Decision Support Systems*, 22(4):307–323, 1998.
3. K.J. Arrow. *Social Choice and Individual Values*. Yale University Press, New Haven CT, 1963.
4. P.P. Bonissone and K.S. Decker. *Selecting Uncertainty Calculi and Granularity: An Experiment in Trading-Off Precision and Complexity*. In L.H. Kanal and J.F. Lemmer, Editors., Uncertainty in Artificial Intelligence. North-Holland, 1986.
5. G. Bordogna, M. Fedrizzi, and G. Pasi. A linguistic modeling of consensus in group decision making based on OWA operators. *IEEE Trans. on Systems, Man and Cybernetics, Part A: Systems and Humans*, 27:126–132, 1997.
6. C.T. Chen. Applying linguistic decision-making method to deal with service quality evaluation problems. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems*, 9(Suppl.):103–114, 2001.
7. G.V. Civille and J. Seltsam. Sensory evaluation methods applied to sound quality. *Noise Control Engineering Journal*, 51(4):262–270, 2003.
8. Bouyssou D., Marchant T., Pirlot M., Perny P., and Tsoukia's A. *Evaluation and Decision Models: A critical perspective*. Kluwer Academic Publishers, 2000.

9. R. Degani and G. Bortolan. The problem of linguistic approximation in clinical decision making. *International Journal of Approximate Reasoning*, 2:143–162, 1988.
10. M. Delgado, J.L. Verdegay, and M.A Vila. On aggregation operations of linguistic labels. *International Journal of Intelligent Systems*, 8:351–370, 1993.
11. G.B. Dijksterhuis. *Multivariate Data Analysis in Sensory and Consumer Science, Food and Nutrition*. Press Inc. Trumbull, Connecticut, USA, 1997.
12. P. Dillon, W. Moody, R. Bartlett, P. Scully, R. Morgan, and C. James. Sensing the fabric: To simulate sensation through sensory evaluation and in response to standard acceptable properties of specific materials when viewed as a digital image. *Proceedings Lecture Notes In Computer Science*, 2058:205–217, 2001.
13. C.R. Han, C. Lederer, M. McDaniel, and Y.Y. Zhao. Sensory evaluation of fresh strawberries (fragaria ananassa) coated with chitosan-based edible coatings. *Journal Of Food Science*, 70(3):172–178, 2005.
14. F. Herrera and E. Herrera-Viedma. Linguistic decision analysis: Steps for solving decision problems under linguistic information. *Fuzzy Sets and Systems*, 115:67–82, 2000.
15. F. Herrera, E. Herrera-Viedma, L. Martinez, F. Mata, and P.J. Sanchez. *A Multi-Granular Linguistic Decision Model for Evaluating the Quality of Network Services*. Intelligent Sensory Evaluation: Methodologies and Applications. Springer, Ruan Da, Zeng Xianyi (Eds.), 2004.
16. F. Herrera and L. Martínez. A 2-tuple fuzzy linguistic representation model for computing with words. *IEEE Transactions on Fuzzy Systems*, 8(6):746–752, 2000.
17. F. Herrera and L. Martínez. A model based on linguistic 2-tuples for dealing with multigranularity hierarchical linguistic contexts in multiexpert decision-making. *IEEE Transactions on Systems, Man and Cybernetics. Part B: Cybernetics*, 31(2):227–234, 2001.
18. F. Herrera, L. Martínez, and P.J. Sánchez. Managing non-homogeneous information in group decision making. *European Journal of Operational Research*, 166(1):115–132, 2005.
19. A. Jiménez, S. Ríos-Insua, and A. Mateos. A decision support system for multiattribute utility evaluation based on imprecise assignments. *Decision Support Systems*, 36(1):65–79, 2003.
20. J. Kacprzyk and S. Zadrozny. Computing with words in decision making: Through individual and collective linguistic choice rules. *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems*, 9(Suppl.):89–102, 2001.
21. J. Lawry. A methodology for computing with words. *Internation Journal of Approximate Reasoning*, 28:51–89, 2001.
22. HS Lee and M. O'Mahony. Sensory evaluation and marketing: measurement of a consumer concept. *Food Quality And Preference*, 16(3):227–235, 2005.
23. E. Levrat, A. Voisin, S. Bombardier, and J. Bremont. Subjective evaluation of car seat comfort with fuzzy set techniques. *International Journal of Intelligent Systems*, 12:891–913, 1997.
24. C.M. Liu, M.J. Wang, and Y.S. Pang. A multiple criteria linguistic decision model (mcldm) for human decision making. *European Journal of Operational Reseach*, (76):466–485, 1994.
25. A.C. Marquez and C. Blanchar. A decision support system for evaluating operations investments in high-technology business. *Decision Support Systems*, 41(2):472–487, 2006.
26. S.A. Orlovsky. Decision-making with a fuzzy preference relation. *Fuzzy Sets Systems*, 1:155–167, 1978.
27. J. Pearce. Sensory evaluation in marketing. *Food Technology*, 34(11):60–62, 1980.
28. M. Roubens. Fuzzy sets and decision analysis. *Fuzzy Sets and Systems*, 90:199–206, 1997.
29. D. Ruan and X. Zeng (Eds.). *Sensory Evaluation: Methodologies and Applications*. Springer, 2004.
30. H. Stone and J.L. Sidel. *Sensory Evaluation Practice*. Academic Press Inc., San Diego, CA, 1993.
31. V. Torra. The weighted OWA operator. *International Journal of Intelligent Syatems*, 12:153–166, 1997.
32. J. Wang, J.B. Yang, and P. Sen. Multi-person and multi-attribute design evaluations using evidential reasoning based on subjective safety and cost analyses. *Reliability Engineering and System Safety*, 52(2):113–129, 1996.
33. P.P. Wang(Ed.). *Computing with Words*. Wiley Series on Intelligent Systems. John Wiley and Sons, 2001.

34. R.R. Yager. An approach to ordinal decision making. *International Journal of Approximate Reasoning*, 12:237–261, 1995.
35. L.A. Zadeh. The concept of a linguistic variable and its applications to approximate reasoning. *Information Sciences, Part I, II, III*, 8,8,9:199–249,301–357,43–80, 1975.
36. L.A. Zadeh. Fuzzy logic = computing with words. *IEEE Transactions on Fuzzy Systems*, 4(2):103–111, May 1996.
37. X. Zeng, Y. Ding, and L. Koehl. *Intelligent Sensory evaluation: Methodologies and Applications*, chapter A 2-tuple Fuzzy linguistic model for sensory fabric hand evaluation, pages 217–234. Springer, 2005.