A review on intelligent sensory modelling

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Abstract. Sensory evaluation plays an important role in the quality control of food productions. Sensory data obtained through sensory evaluation are generally subjective, vague and uncertain. Classically, factorial multivariate methods such as Principle Component Analysis (PCA), Partial Least Square (PLS) method, Multiple Regression (MLR) method and Response Surface Method (RSM) are the common tools used to analyse sensory data. These methods can model some of the sensory data but may not be robust enough to analyse non-linear data. In these situations, intelligent modelling techniques such as Fuzzy Logic and Artificial neural network (ANNs) emerged to solve the vagueness and uncertainty of sensory data. This paper outlines literature of intelligent sensory modelling on sensory data analysis.

1. Introduction
Sensory evaluation has been defined as a scientific method used to evoke, measure, analyse, and interpret responses to products as perceived via the senses of sight, smell, touch, taste and hearing [1]. It plays an important role in the quality control of various food productions. Quality of foods encompass many aspects, such as nutritional value, storage stability, safety and sensory quality. The ultimate criterion of sensory evaluation is how customers respond to the food product. Generally, sensory evaluation involved the application of well-established experimental design together with statistical analysis of sensory data.

Sensory attributes on sensory evaluation normally include aroma, appearance, flavour, mouthfeel and taste. These sensory data are uncertain and vague as the response of consumer are relatively subjective. Their responses are greatly influenced by their eating habits, testing ability, testing environment and even their culture [2]. There are three types of sensory testing methods used, which are discrimination test, descriptive testing and affective testing. Discrimination test determines the sensory difference between each of the samples; descriptive test determines the nature or properties of the sensory difference, descriptive test sometimes relates to the sweetness, crispness, hardness of the...
food samples; affective test determines the intensity of preferences of the customers about the food [3,4]. In sensory evaluation, the common scale for acceptance testing is the 9-point hedonic scale that was developed by Peryam and Pilgrim. The sensory panel is required to give opinion in numerical values from 1 to 9 to different types of sensory attributes. The number “1” of the scale normally elucidates ‘extremely dislike’ and the number “9” is ‘extremely like’ [1]. However, the hedonic scale is not considered the comparison of the evaluator preference towards the different quality attributes, for examples, in judging the sensory quality of the pumpkin, some of the evaluators may feel that hardness of the pumpkin is more important than color or taste of the pumpkin [5].

For sensory data obtained from different groups of panel, the corresponding mathematical models and the data processing procedures are different. This is because the reliability of the sensory data will influence the final output of the products from the mathematical modelling. The sensory evaluation is based on the knowledge acquired in a sensorial way by the panel of experts that participate in the evaluation process. A suitable mathematical formulation is quite difficult in this type of problems because human perceptions are subjective and not objective, therefore the assessments provided by the individuals are vague and uncertain. Furthermore, the quality of food is decisively determined by its taste which is extremely difficult to model or sense as it is highly influenced by cultural and personal perceptions [6]. Initially, classical computational techniques used in sensory evaluation were based on statistics and factorial analysis (Principal Component Analysis, Correspondence Analysis, Generalized Canonical Analysis and etc). However these methods are not efficient in 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 [7]. These methods as mentioned earlier will cause important data lost because (1) there often exist non-linear relations in sensory evaluation field, (2) they compute with great number of numerical data only, and (3) classical method cannot interpret physical result precisely. Hence, new methods based on intelligent methods such as fuzzy logic, neural networks, data aggregation, classification, clustering and etc are needed for solving the vagueness related to this field. There are several reason to explain why intelligent technique is more efficient: (1) they can compute numerical and linguistic data together while dealing with the uncertain and vague condition, (2) they can consider the nonlinear relationship in the analysis and (3) they can interpret the physical result in more precise way [8].

Although the physical and chemical properties associated with sensory attributes can be measured by some instrument such as textures analyzers, gas chromatography (GC), high-performance liquid chromatography (HPLC) and etc, but these kind of instrument can only measure the intensity of the sensory attributes, but do not provide information about consumer’s responses or preferences towards the food product. Nevertheless, they are commonly used in the food industry because their results are more reliable and more objective than those from sensory evaluations. There have only been a few attempts to develop mathematical functions to predict sensory data from instrumental data by correlating them with multivariate regressions and artificial neural networks (ANN). The ANN is a highly simplified mathematical description tool and it can be interpreted as an input output non-linear device [9]. ANN is found to have higher predictive capability than RSM model with limited number of experiments [10]. Another intelligent modeling tools called fuzzy logic is used to solve fuzzy variables with uncertainty and imprecision. The following section will further discuss the introduction and application of intelligent sensory modelling.

2. Fuzzy Logic
Fuzzy logic can be used to convert linguistic data to numerical values. Linguistic data obtained from sensory test are naturally fuzzy and uncertain. The Fuzzy set theory was first proposed in 1965 by Zadeh [11]. Zadeh created this theory that could cover fuzzy variables with uncertainty and imprecision, like linguistic expressions and their relation. Recently, many successful cases of fuzzy set applications can be found in the existing literature, such as pattern recognition, classification, chemical plants, automobiles, fermentation and etc [11]. In the field of food science, several research papers highlighted the application of fuzzy logic on sensory evaluation and food process control [8,11–13].
However, the understanding and applications of fuzzy theory are still scarce in the field of sensory data. The experimental element influenced more than theoretical element in the field of food sensory science. Hence, the application of fuzzy theory has great potential in this field, as sensory data provided are either crisp data or approximate data.

2.1 Theory
Fuzzy logic uses Fuzzy Sets to convert the linguistic data to mathematical data. Fuzzy sets are denoted into several ways. The first is with discrete elements such as the following:

\[ A = \{(\mu_{A,i}, X_i)\}, \forall X_i \in X (i = 1, 2, 3, ..., n) \]  
\[ A = \mu_{A,1}/X_1 + \mu_{A,2}/X_2 + \cdots + \mu_{A,n}/X_n (i = 1, 2, 3, ..., n) \]  

where \( X_i \) and \( \mu_{A,i} \) are the set elements and their membership degrees, respectively, and in the second equation, plus (+) does not mean arithmetic addition. Second, fuzzy sets are denoted with continuous element as follows:

\[ A = \{(\mu_A(X), X)\}, \forall X \in X \]  

where \( \mu_A(X) \) is the membership function and \( X \) is the element in continuous variables. Membership functions are typically given in three types: triangle, trapezoid, and bell shapes (Figure 1). Membership degrees ranges from 1 to 0.

When designating fuzzy set partitions, the shape and location of the partitions should be determined properly. Fuzzy sets with wide partitions imply more fuzziness, or uncertainty, and those with narrow partitions have a lesser degree of fuzziness. A fuzzy set with a membership degree of 1 at one element only and 0 at the other elements is equivalent to a deterministic value, and that with a membership degree of 1 at all the element becomes a crisp set [11].

![Figure 1. Pattern of membership functions for fuzzy set.](image)

2.2 Application of Fuzzy Sets on Sensory Data
The intensity or preference of attributes obtained from sensory evaluation can be converted to fuzzy sets in two ways. One is to change the sensory data in numerical form to fuzzy values. Another one is converting sensory data in linguistic or hedonic form to fuzzy values.

Fuzzy values can be defined in the following when sensory data are obtained as numerical (intensity scores):

\[ \text{Fuzzy value} = \{(\text{membership degree})_i/\text{(intensity level)}_i, (\text{membership degree})_2/\text{(intensity level)}_2, \ldots, (\text{membership degree})_n/\text{(intensity level)}_n\} \]
where the intensity level is a sensory score, and its membership degree is the proportion of panelist votes to the total, who rated at the corresponding score.

If the fuzzy values is given in linguistic form, then the panelist vote for the linguistic rating. The vote of the linguistic is correlated as to the membership degree of the linguistic rating. The linguistic levels not just about sensory attributes rating, but also the hedonic or preferences, such as satisfactory, medium, fair and not satisfactory.

2.3 Application of Fuzzy Logic in Sensory Evaluation

Since sensory evaluation are often in linguistic form, fuzzy logic is an important tool whereby vague and imprecise data can be analyzed and concluded according to acceptance, rejection, ranking and the preference of the sensory attributes [5,14–18]. A number of past researches had used Fuzzy logic to analyze sensory data. Perrot et al. [19] provide an overview of the application of fuzzy concepts to the control of the product quality in the food industry over past 10 years. Kavdir and Guyer [20] have also used this approach for apple classification. Martinez [7] discussed the sensory evaluation based on linguistic decision analysis. This analysis shows advantages of using the linguistic 2-tuple decision analysis applied to the sensory evaluation because it provides a guideline for modeling and computing to deal with uncertain and vague information, in a consistent mathematical way. Mukhopadhyay et al. [21] used fuzzy logic to analyze the sensory data responses given by 40 trained panelists regarding the taste, color, aroma and mouthfeel of the chhana podo. The result showed that Fuzzy Logic can be used to validate optimization results obtained from genetic algorithm (GA) (constrained optimization technique). Singh et al. [22] also used this fuzzy approach to analyze the sensory score from 102 panelists that were trained by discussing the definition of quality attributes selected for sensory evaluation, explaining the score sheet and method of scoring. Judges were instructed to tick the respective fuzzy scale factor for each of the quality attributes of the sample after evaluating the samples. The samples were rated as “Not satisfactory,” “Fair,” “Medium,” “Good” and “Excellent.” The set of observations were analyzed using Fuzzy analysis of sensory scores. It was also successfully applied for bread prepared from millet-based composite flour [22]. The combination of triangular membership function in Fuzzy logic and five point sensory scale was also implemented in mango drinks [14], dahi powder [23] and instant green tea powder [17]. Uprit and Mishra [18] also calculated normalized fuzzy membership function for the Soy fortified paneer (SFP) samples prepared from blends containing different proportions of buffalo milk of varying fat content and soy milk for their ranking. Normalized fuzzy membership function also has been adopted on the selected coffee products to determine the best quality attributes and rank the products [15]. Dehjani et al. [5] also investigated the preference of quality attributes, intensity of quality attributes and overall quality attributes of tea liquor by using Fuzzy logic where the intensity and preferences of sensory scales were represented by triangular membership function. Kaushik et al. [24] applied fuzzy logic techniques to analyze the sensory attributes of mango pulp and litchi juice by using triangular membership distributions function for 5-point hedonic scale.

3. Artificial Neural Network (ANN)

ANN is first introduced in 1943 by Warren McCulloch [11]. ANN is very useful in correlating process variables with non-linear relationships, which is commonly found in experimental data from food processing. ANN has been used in food areas associated with sensory test, sensory quality-based food process control, and control set points of processes [12]. ANN also has been applied in food sciences such as classification of food products [25–27], monitoring authenticity of low-fat yogurt [28], and honey [29], prediction of optimum conditions of frozen cooked rice associated with sensory evaluation [30], evaluation of extra virgin olive oil stability [31], pattern recognition [32], electric nose, machine vision [33], and etc. Most of the application of ANN is not directly correlated sensory attributes with process variables, but using sensory scores with relevant data.
Hybrid type model combining Fuzzy Logic and ANN, which is called Fuzzy Neural Network (FNN) has also been developed. It is reported that FNN is a more powerful approach than ANN itself [34]. FNN has been compared with RSM and MRA (Multiple Regression Analysis) and FNN shows a great accuracy for estimation sensory evaluation scores [34,35].

3.1 Theory

ANN is a network that consists of many neurons that carry non-linear function, and different unit that contains different function are weighted, connected together and combined to produce overall output. ANN consists of input layer, hidden layer and output layer as shown in Figure 2. Before applying ANN, the input and output variables should be established. Next, the type of ANN should be chosen, such as radial basis function, Kohonen self-organizing, recurrent, modular and so on. Input variables are inserted in the first layer, and the calculation steps proceed layer by layer until the last layer. The signals propagate from input to output layer. The hidden layer may affect the accuracy, hence, it is necessary to reasonably determine the hidden layer when they are more correlations between variables [11].

![Figure 2. Schematic representation of a multilayer feed-forward ANN.](image)

Each input layer is multiplied with their weight, and the product are summed. The sum deducted by Threshold, which is net, is the input to the transfer function and subsequently produce output value from the neuron. The function can be non-linear function such as sigmoid function, step function and etc. It is necessary to optimize the weight in order to obtain better prediction. Consequently, the training or learning process adjusts the weights by altering them until the errors between outputs given for the training is minimized. This can be done by applying Back-Propagation ANN Algorithm and the weight is changed iteratively [26]. The errors are propagated backwards from final output to input layer.

3.2 Application of ANN on Sensory Data

ANNs have been used for many purposes in food technology especially food classification such as rice [32], cheese [36], coffee [37], eggplant [38], honey [39], tea [40], wine [41,42], fruit beverages [43,44], beer [45] and other alcoholic drinks [46,47]. Bahramparvar et al. [48] used ANN method to predict the total acceptance of ice-cream. The sensory attributes (appearance, flavor, body and texture, coldness, firmness, viscosity, smoothness and liquefying rate) were used as inputs and independent total acceptance was the output of the ANN. Raju Krishnamurthy [49] compared ANN modelling techniques with conventional statistical method such as Multiple Regression Analysis (MRA) to predict consumer liking scores from trained sensory panel scores regarding the 10 market samples of beef bouillon products. Cruz et al. [50] used Levenberg–Marquardt training algorithm with the hyperbolic function as the activation function in the hidden layer and the linear function in the output layer to identify the acceptability and purchase intent of probiotic yoghurt. Tominaga et al. [34]...
utilized integration of Fuzzy set theory with ANN to predict the most suitable blending ratio of coffee and its shows a positive result.

4. Conclusions
It is very important to analyze the sensory data obtained from sensory evaluation of food product for marketing purposes, for product control and quality control purposes in food industry. However, there are some difficulties in analyzing these sensory data which are vague and uncertain. Furthermore, human sensory response is relatively subjective and this causes the objective quantification a more difficult task.

Statistical methods for sensory evaluation have been implemented and widely used. However, this method is only suitable to analyse sensory data that have numerical value but not linguistic data. Hence, other methods such as Fuzzy Logic are developed to directly quantify the linguistic data and hence more convenient to analyse the primary data from sensory evaluation. ANN is also one of the intelligent techniques to predict the non-linear relationships between process variables and the sensory data. FNN is suggested to be applied to combine the advantage of Fuzzy Logic and ANN together. FNN is potentially more effective because Fuzzy Logic can solve fuzzy data while ANN can correlate non-linear relationships from sensory test.

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