FUZZY-RULE-BASED APPROACH FOR MODELING SENSORY ACCEPTABITITY OF FOOD PRODUCTS

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ABSTRACT

The prediction of product acceptability is often an additive effect of individual fuzzy impressions developed by a consumer on certain underlying attributes characteristic of the product. In this paper, we present the development of a data-driven fuzzy-rule-based approach for predicting the overall sensory acceptability of food products, in this case composite cassava-wheat bread. The model was formulated using the Takagi-Sugeno and Kang (TSK) fuzzy modeling approach. Experiments with the model derived from sampled data were simulated on Windows 2000XP running on Intel 2Gh environment. The fuzzy membership function for the sensory scores is implemented in MATLAB 6.0 using the fuzzy logic toolkit, and weights of each linguistic attribute were obtained using a Correlation Coefficient formula. The results obtained are compared to those of human judgments. Overall assessments suggest that, if implemented, this approach will facilitate a better acceptability of composite bread.

Keywords: Fuzzy-Rule, Sensory analysis, Composite cassava wheat (CCW) bread, Food product

1 INTRODUCTION

Sensory analysis is often used as an important tool in evaluating how processing and product formulation affect the acceptability or preference of food products. Judgment about a product is often made by a group of assessors either trained or untrained based on predetermined quality attributes pertinent to such product. The sensory data obtained through subjective evaluation is normally analyzed statistically. Using this method, a complex idea of product quality is often generated, which makes it nearly impossible to determine the strength and weakness of the product regarding its sensory attributes (Sundaram et al., 2004). There is need for a model of human reason that does not require complex mathematical construction for sensory evaluation.

Fuzzy logic is an important decision making tool that has recently found wide application in the study of various physical and biological systems. The concept of fuzzy set theory is to treat uncertain phenomena mathematically, i.e., expressing the degree of ambiguity in human thinking and relating it to quantitative data. Sensory analysis of a food product is certainly an ambiguous task due to differences in the individual panelist's perception of the product's attributes. There are three main advantages in using fuzzy logic, especially in this situation. First, the system needs not be modeled using complicated mathematical construction. Second, expert experience, here for sensory analysis of a food system, in the form of natural language can easily be coded as fuzzy rules for describing the overall behavior of the system. Finally, system behavior can be easily and rapidly implemented and tuned. Consequently, future product modifications can be achieved easily.

The objective of this work is to develop an approach that can be used to determine the overall acceptability of bread samples, from sensory scores of separate product attributes, using a fuzzy inference system instead of human assessments. The present paper discusses the development of a data-driven fuzzy-rule-based sensory analysis of cassava wheat bread. We focus on the Fuzzy-Rule-Based System (FRBS), which includes fuzzy membership functions and rule generation. The gain of this exercise is not only in reducing the human error in achieving the final decision about the overall acceptability, but also in assisting with future decisions as to what processing condition should be used in improving this kind of product.

Other tools have been used to develop expert systems for describing the behavior of biological systems, e.g., in recent times, an artificial neural network (ANN) has also been proposed and applied in agriculture and food engineering. Although they are able to model non-linear systems, the tendency of ANNs to get stuck at a local optimum performance instead of better global performance (Lau, Wong, & Ning, 2001; Lee, 1990) has made them unsuitable for the kind of application required in some food engineering projects.

In addition, fuzzy logic is conceptually easy to understand, flexible, and tolerant of imprecise data. The approach can model complex non-linear behavior of any system under study. Fuzzy logic modeling techniques can be classified into three categories, namely, Linguistic, Relational Equation, and Tagaki, Sugeno, and Kang (T-S-K) (Tagaki & Sugeno, 1985; Sugeno & Kang, 1998). The major difference among these approaches is in the way the consequences of rules are computed. We adopted the T-S-K approach because it has shown to be effective in modeling non-linear dynamic systems (Johansen & Babuska, 2003).

2 A DATA-DRIVEN FUZZY-RULE-BASED SYSTEM

Data-driven rules are the fuzzy "If ... Then …" rules that are generated from a set of training data. The training data used in this research work is the result of sensory scores for samples of bread baked at different times. The data-driven fuzzy-rule-based system (FRBS) and rule induction for handling classification tasks have previously been applied to classification problems. Chen et al. proposed a method for classification of numerical data (Chen et al., 2001). Chen and Lin also proposed a method for classification for the classification of the Saturday Morning problem (Chen et al, 2005).

In summary, Figure 1 shows the architecture of a data-driven fuzzy-rule-based system.

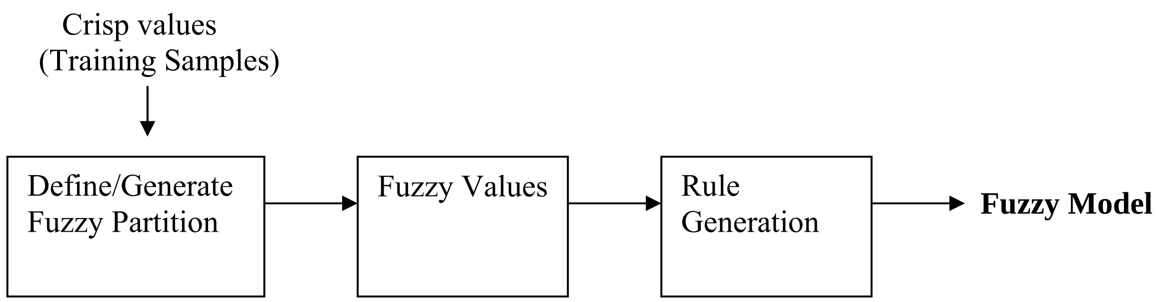


Figure 1. Structure of Fuzzy-Rule generation process

The model that is adopted here for the building of the fuzzy inference system is the Sugeno Fuzzy Model (also known as the TSK model) proposed by Takagi, Sugeno, and Kang (Sugeno & Kang, 1998), which uses a systematic approach to generating fuzzy rules from a given input-output data set. A typical fuzzy rule in a Sugeno fuzzy model has the form:

$$\text{IF X is A AND Y is B THEN } Z = f\,(X, Y). \tag{1}$$

A and B are fuzzy sets in the antecedent, while f (X, Y) is a crisp function in the consequent and a polynomial in the input variables x and y. It can be any function as long as it can appropriately describe the output of the model within the fuzzy region specified by the antecedent rule (Jang, 1997). Equation 1 may be rewritten in the form

$$\text{IF } X_1 \text{ is } A \text{ AND } X_2 \text{ is } B \text{ AND……AND } X_N \text{ is } H \text{ THEN } Z = f(X_1, X_2,\ldots X_N). \tag{2}$$

The coefficients (weights of the attributes) of the function f above are determined from simulation of the training data set of the phenomenon to be modeled. The weights for each linguistic term are considered as a quantifier "some" or "all." If the weight = 1, the quantifier is regarded to be "all;" otherwise it is considered to represent "some." The extent to which "some" is interpreted depends on the value of the weights of the respective linguistic terms. In running the FRBS that employs such learned rules, however, the concluding classification is that of the rule whose overall weight is the highest.

In this method, the relationship between each attribute and the overall model acceptability is determined using multiple regression analysis. This method is adapted from the statistical methodology of modeling an entity dependent on multiple factors. Suppose we have data sets with variable Y_i depending on X_{ij} where X_{ij} are the determinant factors. Then we can express Y_i in terms of X_{ij}.

$$E[Y_i] = \sum_{j=0}^{m} B_j X_{ij} \tag{3}$$

where $B_j = (X'X) - X'Y$ and X = matrix X_{ij} and Y = vector Y_i.

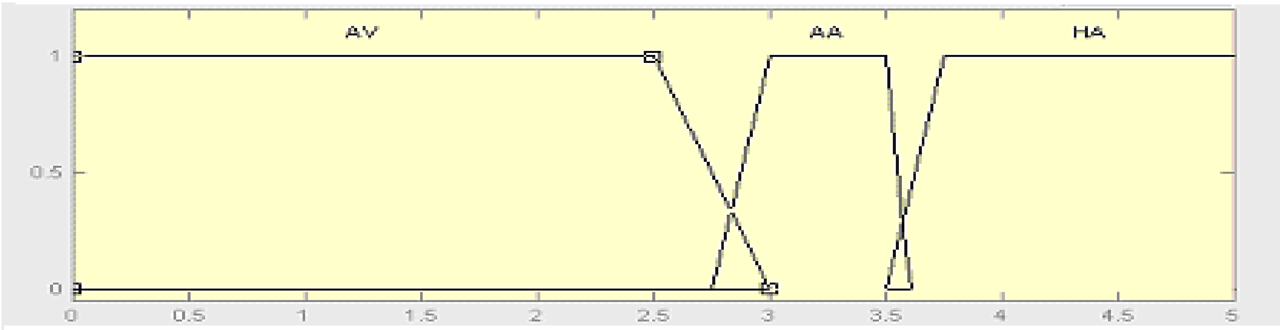
In our case, the entries in X_{ij} and Y_i are fuzzy membership values of the attributes of the bread sample and overall acceptability, respectively. The corresponding B_j for each level of overall acceptability is used as weight for the determinant. Note that B_j values are the coefficients of each factor (sensory attributes) used in determining the overall acceptability.

The procedure used for determining the fuzzy rules for the sensory acceptability of the wheat bread is detailed below:

1) *Calculate fuzzy membership values for each linguistic variable in the domain of overall acceptability*
2) *Define the fuzzy partitions using predefined criteria for evaluation*
3) *Calculate the weights of each variable using Equation 3.*
4) *Create rules.*
5) *Test the rule set.*

3 EXPERIMENTAL DESCRIPTION

In this section, we describe our use of the fuzzy-rule-based approach to determine which characteristics are most important for determining bread acceptability. Bread samples were produced as described in Shittu et al. (2007). The bread samples were evaluated by ten trained panelists recruited from the staff and students of the Department of Food Science and Technology, University of Agriculture, Abeokuta, Nigeria. The panelists were instructed to use a five-point hedonic scale (1= Dislike extremely, 5= like extremely) to evaluate acceptability of sensory attributes such as taste, crust and crumb color, crumb structure, crust thickness, doneness, and overall acceptability. From the result, it was obvious that most of the samples were acceptable. Also, the fuzziness of the judgments is obvious. The fuzzy rule-based method developed in this work was used to classify the overall acceptability into three levels (Figure 2) because of the variations of the data from the center of the values. Also, the three levels and their ranges were suggested by consensus of experts in the Department of Food Science and Technology, and used to determine the membership function for the attributes and the overall acceptability.



Sensory Scores

Figure 2. The Fuzzy Membership Function (MF) for the sensory scores. AV is low; AA is average, and HA is high.

The data were obtained from the sensory scores on cassava wheat bread baked at different combinations of temperature and time. The scores are rated by 10 trained evaluators. The mean of the scores rated for each attribute of the bread are given in Table 1 below.

Table 1. Results of Sensory Tests (Attribute results range from 1 = dislike extremely to 5 = like extremely)

TEST NUMBER	BREAD SAMPLES	TASTE	DONENESS	CRUST COLOR	CRUMB COLOR	CRUMB STRUCT.	CRUST THICK.	OVERALL ACCEPT.
1	215°C + 45min	2.2	3.7	2.2	3.0	3.8	2.2	2.7
2	190°C + 24min	2.8	3.0	2.3	3.0	3.2	2.2	2.6
3	215°C + 32.5min	2.9	3.8	3.7	3.6	3.5	3.6	2.9
4	233°C + 24min	3.3	3.5	3.2	3.5	3.3	3.3	3.2
5	190°C + 41min	3.1	3.7	3.2	3.4	3.4	3.7	3.6
6	215°C + 20min	4.1	3.7	3.2	3.4	3.4	3.7	3.9
7	197°C + 41min	3.4	4.4	3.4	4.0	3.4	3.9	3.5
8	197°C + 24min	3.9	3.6	3.6	3.8	3.8	3.3	3.6
9	215°C + 32.5min	3.2	3.9	2.5	3.6	3.5	3.6	3.4
10	240°C + 32.5min	3.5	4.2	3.8	4.2	3.2	4.0	3.7

Source: *Department of Food Science and Technology, University of Agriculture, Abeokuta Nigeria*

The data above are partitioned into three different categories, Low, Average and High using overall acceptability as the criterion for the partition. For easy computation, labels are used to connote the linguistics terms. The label used to connote each linguistic term in the sensory dataset are given in Table 2. Each sensory score in Table 1 is mapped to the graph in Figure 2 to obtain the membership function value.

AV, AA and HA connote a rank of low, average, and high respectively. Certain attributes have zero coefficients in

Table 2. Linguistic terms in the data set

LINGUISTICS TERMS	LABEL
Taste is AV	T1
Taste is AA	T2
Taste is HA	T3
Doneness is AV	D1
Doneness is AA	D2
Doneness is HA	D3
Crust Color is AV	CC1
Crust Color is AA	CC2
Crust Color is HA	CC3
Crumb Color is AV	CRC1
Crumb Color is AA	CRC2
Crumb Color is HA	CRC3
Crumb Structure is AV	CS1
Crumb Structure is AA	CS2
Crumb Structure is HA	CS3
Crust Thick. is AV	CT1
Crust Thick. is AA	CT2
Crust Thick. is HA	CT3

the domain for some levels of overall acceptability. Such attributes are assigned zero weight. To test for the effectiveness of the generated rule set, eight of the 10 experiments are used to generate the rule while the other two are used to test for the validity of the rule set. Using the algorithm that has been designed for the FRBS, we model the sensory data of cassava wheat bread and generate two rules that can be used for classification into three levels of acceptability using the linguistics variables. The results shown in Tables 3 to 5 represent the membership scores obtained following the steps in the fuzzification procedure highlighted above.

Table 3. Membership score for acceptability is Low (AV) for each sensory attribute of CCW bread

Taste (T1)	Crust Color (CC1)	Crust Thickness (CT1)	Overall Acc.
1	1	1	0.6
0.4	1	1	0.8
0.2	0	0	0.2
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0

Table 4. Membership scores for acceptability is Average (AA) for each sensory attribute of CCW bread

Taste	Doneness	Crust color	Crumb color	Crumb cell Structure	Crust Thickness	Overall Acc.
0	0	0	1	0	0	0
0.2	1	0	1	1	0	0
0.6	0	0	0	1	0	0.6
1	1	1	1	1	1	1
1	0	1	1	1	0	0
0	0	1	0	0	0	0
1	0	1	0	1	0	1
0	0	0	0	0	1	0

Table 5. Membership scores for acceptability is High (HA) for each sensory attribute of CCW bread

Taste	Doneness	Crust color	Crumb color	Crumb cell Structure	Crust Thickness	Overall Acc.
0	0.8	0	0	1	0	0
0	0	0	0	0	0	0
0	1	0.8	0.4	0	0.4	0
0	0	0	0	0	0	0
0	0.8	0	0	0	0.8	0.4
1	0.8	0	1	1	0.4	1
0	1	0	1	0	1	0
1	0.4	0.4	1	1	0	0.4

Next, we generate the following regression models predicting the overall acceptability of the bread samples for each level of acceptability:

Low acceptability (Rule 1): $0.267 - 0.333\ T1 + 0.667*CT1$

Average acceptability (Rule 2): $0.56 - 0.15*T2 + 0.90*D2 + 0.78*CC2 - 0.78*CRC2 - 0.49*CS2 - 0.34*CT2$

High acceptability (Rule 3): $0.024 - T3 + 0.962 * D3 + 0.607 * CC3 + 0.746 * CS3 + 1.131 * CT3$

The validity of the rule generated from sensory data of samples 1 to 8 above is then tested using the original sets of data for bread samples 9 and 10. The steps followed are illustrated as shown below. For sample 9, the scores for each sensory attribute are:

Taste	Doneness	Crust color	Crumb color	Crumb Structure	Crust thick	Overall acc
3.2	3.9	2.5	3.6	3.5	3.6	3.4

We transform the scores into their equivalent fuzzy membership values.

T1 =0.0 D1= 0.0 CC1= 1.0 CRC1=0.0 CS1=0.0 CT1= 0.0

T2 =1.0 D2= 0.0 CC2= 0.0 CRC2=0.0 CS2=1.0 CT2= 0.0

T3 =0.0 D3=1.0 CC3= 0.0 CRC3=0.4 CS3=0.0 CT3= 0.4

Substituting the values into the premises we find:

Rule 1: 0.267-0.333*0.0 + 0.67*0.0 = 0.267

Rule 2: 0.56 + 0.15*0.0 + 0.90*0.0 + 0.78*0.0 - 0.78*0.0 + 0.49*1.0 + 0.34*0.0 = 0.07

Rule 3: 0.024 – 0.228*0.4 + 0.962*1.0 + 0.607*1.0 + 0.746*0.0 + 1.131*1.0 = 0.71

The final rule is that with the highest value. **(Rule 3)**

4 EVALUATION

The fuzzy-rule-based system was evaluated using randomly selected samples from the existing data sets. Our observation after comparing the human-subjective method and fuzzy-rule-based system revealed that when a food product (a cassava wheat bread) of 215^0C and 32.5 minutes was used, both systems gave the same level of acceptability (average). Again, when tested under 240^0C and 32.5 minutes both human and fuzzy classification gave high acceptability. It was concluded that the fuzzy rule-based approach for modeling sensory acceptability of food products has an economic advantage over the classic human-judgment approach.

5 CONCLUSION & FUTURE WORKS

It might be necessary to redesign this system in a way that it will be deployable and usable without MATLAB. It might be necessary to use an adaptive fuzzy logic technique when it comes to the improvement of the nutritional value of food products. We have been able to design a Fuzzy Inference system (FIS) used to evaluate sensory acceptability of food products. Finally, this novel approach is a path towards reliable evaluation of sensory-based food quality assessment and should be considered a significant activity by the food scientists and processors alike. Generating rules for bread and other food producers to improve the acceptability of their products not only offers potential economic advantage for the producer but may also open new pathways for quality and nutritional improvements. For populations where urbanization might provide nutritional challenges, such improvements could have significant individual and public health benefits.

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