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Fusion of electronic nose and tongue response using fuzzy based approach for black tea classification

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Abstract

Automation for tea quality estimation is a challenging task and with the advent of electronic nose and electronic tongue systems this problem becomes quite addressable by instrumental means. Electronic nose judges tea sample based on aroma of the sample and based on taste tea quality can be classified using electronic tongue. For estimation of flavour of tea rather the overall quality of tea can be estimated if these two sensory responses can be fused. In this work, we have attempted to fuse these two sensory features using fuzzy fusion technique. A general fuzzy rule base is developed from the transient datasets obtained from electronic nose and tongue separately. The fuzzy system model can give accurate prediction with much simpler model than neural network. But both the system has certain advantages. In order to develop better classifier fuzzy neural network (FNN) model is also developed. Moreover the model works with transient responses and no data compression technique is employed. It is found that the combined sensor signature regarding tea quality estimation is quiet improved compared to individual sensor systems for all three classifiers and among these FNN is the best suited model for tea classification.

*Keywords:*Electronic nose; electronic tongue; fuzzy fusion ; neural network; fuzzy neural network

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1. Introduction

Tea quality judgment is a very challenging task due to multidimensional attributes of tea. Like human taster simultaneous utilization of aroma and taste sense will give better discrimination and that is already applied in several areas [1-3]. Authors have reported the research work on tea quality analysis based on fusion of these two sensor responses using neural network [4].Here we have attempted to fuse two sensory responses and analyzed using three different classifiers. The fusion techniques attempted in this work is based on fuzzy logic and neural network. This work has two fold objectives: One to show that combined sensor perception is quite improved than individual sensor system. Second is to develop multiple classifiers and to find whichever is better for our system.

Combination of sensory systems showed improvement compared to the individual systems in various applications. For superior characterization of red wines [5], three sensory modalities were combined - an array of gas sensors, an array of electrochemical liquid sensors and an optical system to measure color. For identifying flavor, which is a combined perception of aroma and taste, a combination of electronic nose and electronic tongue sensors based on SAW devices were used [6]. Analysis of different degrees of bitterness of olive oils using a combined system was carried out in [2], where the capability of discrimination of the combined system was reported to be superior to that obtained with the three instruments separately and a good correlation was found between the bitterness index (evaluated by a panel of experts) and the scores obtained from the combined electronic panel. In [7] authors have developed five different classifiers to classify potato cream and chips using electronic nose and tongue. They also found for all classifiers the combined sensor system provides better result compared to individual sensor system.

Fuzzy logic and neural networks are complementary technologies. They work at different levels of abstraction and individually provide rich functionality, which even bought together in a cohesive fashion provide us with "intelligent" systems. A combination of these two technologies endows systems with a two fold advantage. Fuzzy logic provides a high level framework for appropriate reasoning that can appropriately handle both the uncertainty and imprecision in linguistic semantics, model expert heuristics, and provide requisite high organizing principles. Neural networks provide self-organizing substrates for low level representation of information with on-line adaptation capabilities. It therefore seems both plausible and justified to attempt combining both these approaches in the design of intelligent systems.

Proposed Scheme for this work

For the black tea quality evaluation, tea taster gives the marks against "liquor" which is the combined perception of taste, briskness, and astringency of the sample and we implement it using electronic tongue. The scores assigned to "aroma" signify the smell and flavour of the samples and that can be implemented by using electronic nose. Classification of samples from the obtained set of data is a major task.

A classifier is an algorithm that assigns a class label to an object, based on the object description. It is also said that the classifier predicts the class label. The object description comes in the form of a vector containing values of the features (attributes) deemed to be relevant for the classification task. Typically, the classifier learns to predict class labels using a training algorithm and a training data set. A classifier can be designed when a training data set is not available by using its prior knowledge and expertise. Once trained, the classifier is ready for operation on unseen objects. One possible definition of a fuzzy classifier is given in [8] as 'Any classifier that uses fuzzy sets or fuzzy logic in the course of its training or operation'.

In this work we have developed three different types of classifier and with all classifiers we have attempted the datasets obtained from electronic nose, electronic tongue and combined dataset from both the sensor systems. All three classifiers are explained clearly in data analysis section. Due to the presence of innumerable chemical components tea classification is much more complicated problem than any other pure food sample. Data collection and data fusion method are shown in flow diagram of Fig.1.

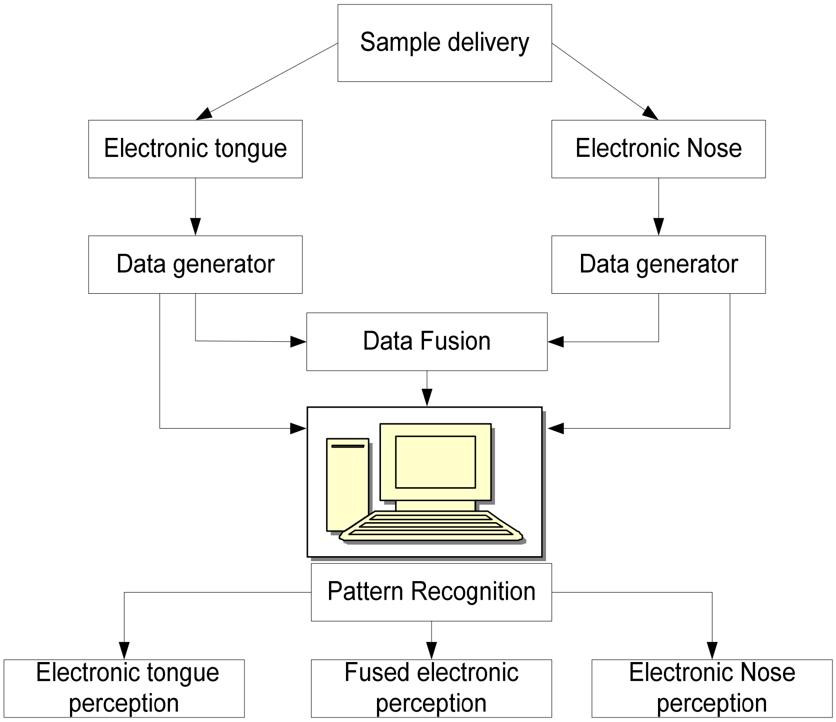


Fig.1: Flow diagram of the work

2. Experimentation

Experiments have been carried out with 48 finished black tea samples of four different grades of Indian tea. For each sample, 5 replicated measurements have been taken. Thus 240 readings each for electronic nose and electronic tongue are available for analysis. As the expert tea taster grades the tea samples and according to increasing order grading we considers four tea grades are CLASS1 to CLASS4.
The electronic nose has five MOS sensors from Figaro in the array and the voltammetric electronic tongue uses a three electrode standard configuration with the working electrodes made of platinum, palladium, rhodium, gold and iridium. The entire transient response for each sensor is considered for analysis. The electronic nose and tongue sensors used in this work are described in detail in [9, 10].The experimental conditions used for electronic nose and tongue is given in [4].

3. Data Analysis

Tasting of tea is a highly specialized job and calls for multidimensional sensory capabilities like finer senses of taste and smell, experienced analytical skill, and ultra sensitive classification ability. As a first step to identify underlying clusters in the electronic sensor signatures, the data obtained from each individual electronic sensor systems and the merged data are analyzed using principal component analysis (PCA).

3.1. Principal Component Analysis (PCA)

Principal component analysis [11] has been widely used in modeling the statistics of a set of multi-dimensional data. This linear feature extraction technique reduces dimensionality of data with a minimum loss of information. By using PCA, data may be expressed and presented in such a way as to highlight their similarities and differences. PCA achieves this by computing the eigenvectors and eigenvalues of the covariance matrix of the dataset.

3.2. Separability index (SI)

A cluster separability criterion [12] has been used in our study for quantitative measurement. The separability index is defined by the ratio of the trace of the 'between class scatter matrix' (SB) to that of the 'within class scatter matrix' (SW), and the expressions are given below:

$$S_B = \sum_{i=1}^{c} (m_i - m)(m_i - m)^T \tag{1}$$

$$S_W = \sum_{i=1}^{c} \left(\sum_{j=1}^{n_i} (x_{i,j} - m_i)(x_{i,j} - m_i)^T \right) \tag{2}$$

$$m = \frac{1}{c} \sum_{i=1}^{c} m_i \tag{3}$$

where, c is the number of classes,
m = mean of the entire dataset
m_i = mean vector of class i, i = 1,2, …..c
n_i = number of samples within class i, i = 1,2, …..c
$x_{i,j}$ = jth sample of ith class

3.3. Neural Network Framework using BPMLP Topology

A three layer BP-MLP model with one input layer, one hidden layer, and one output layer has been considered [13, 14] as shown in Fig.2. The input layer has been fed with the output from the sensor array, and the output layer has been configured to show the taster's score. While using the electronic nose alone, the artificial neural network has five input nodes as there are five sensors in the multi-sensor array. Since this a four class problem, the output layer of the network needs to be assigned with four nodes. Convergence during the learning process has been obtained with acceptable accuracy with only one hidden layer with eight nodes.

In all the cases, the learning rate of the hidden layer has been kept at 0.01 and 'logsig' is used as the activation function imposed on the hidden layer outputs. 'tansig' has been used as the activation function of the output layer and the learning rate in the output layer is taken as 0.1.

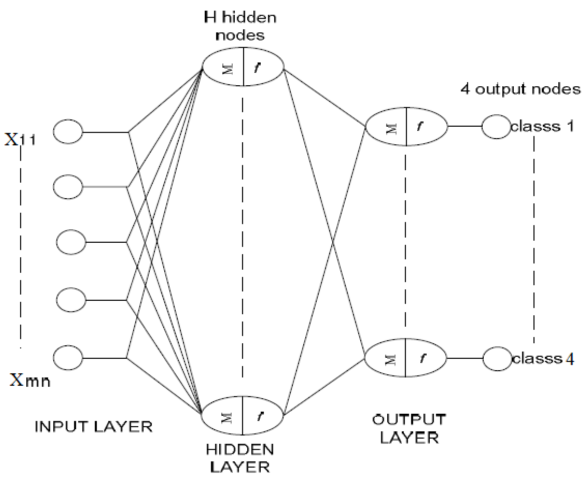


Fig. 2: Neural network model (three-layer MLP network)

Fuzzy Model Framework

The proposed fuzzy classifier model framework is shown in Fig. 3. It follows the Takagi-Sugeno model using Wang-Mendel (WM) Method for generating fuzzy IF-THEN rules from data and to make it a comprehensive and flexible fuzzy system approach to data description and prediction having high prediction accuracy [15] and hence it is suitable for solving the problems based on pattern recognition.

In the Fuzzy network as in Fig. 1, the first layer is the input layer where $S_1, S_2, \ldots S_m$ are the number of sensors. The value of m for electronic nose, electronic tongue and the combined sensory response are 5, 5 and 10 respectively. The next layer, X_{11} to X_{1n}, X_{21} to X_{2n} …. X_{m1} to X_{mn} are transient response of the individual sensors of electronic nose and electronic tongue respectively for all classes where n is the number of samples. For each transient data points membership values and then degrees are calculated following Wang-Mendel method [16].

For i[th] data-point, degree is obtained as $D_i = M_{1i} * M_{2i} * \ldots * M_{mi}$ (4)

The next layer is to create the fuzzy rule base for four classes represented as RB_1, RB_2, RB_3 and RB_4. The rule base is achieved by keeping the rules with highest degree among D_1 to D_n. The last layer is to identify the class where centroid defuzzification strategy is used to determine the grade of the sample which can be within CLASS1 to CLASS4.

$$\text{Calculated grade} = \frac{\sum_{j=1}^{r}(D_j * C_j * cf_j)}{\sum_{j=1}^{r}(D_j)} \quad (5)$$

where, r is the number of fuzzy rule in the fuzzy rule base. D_i = the product of the membership values of each atomic clause in the antecedent, confidence factor, cf_i =1/exp(no. of sensors – no. of matching antecedents) and c_j =center value of output region.

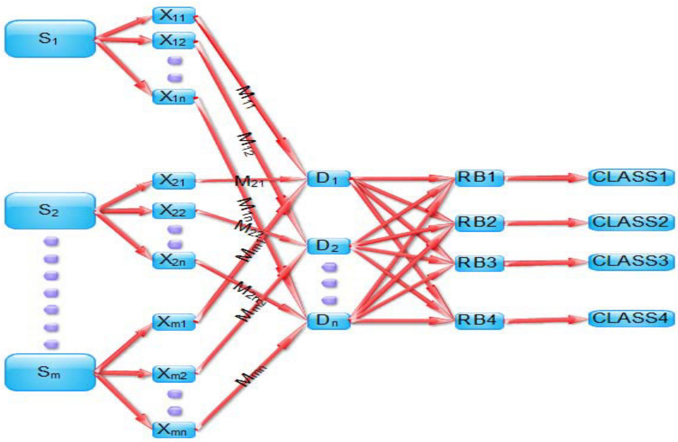


Fig. 3: Proposed Fuzzy fusion model framework

For combining the two sensors system responses, the Gaussian mean for each transient sensor response is considered as the maximum information and fusion is performed with mean data. So for combined system the total no of features are 5+5=10.

3.5. Fuzzy Neural Network (FNN) Model Framework

The neuro-fuzzy computing paradigm [17, 18] represents a careful integration of the merits of the neural network and fuzzy logic technologies in an effort to extend the capabilities of intelligent decision-making systems. Such integrated systems are referred to as fuzzy-neural systems if the fuzzification is performed on neural network architecture, or on its input output space. Integrated fuzzy neural models exploit parallel computation and demonstrate the ability to operate and adapt in both numeric as well as linguistic environments. The development of such integrated models has a common thread that derives from the desire to embed data-driven knowledge into neural network architecture [19, 20] to facilitate fast learning.

Fuzzy neural system architecture is developed as shown in Fig. 4. The fuzzy neural network architecture has four layers. Layer (A) is the input layer. The node equals to the number of sensors. Layer (B) is the membership function generation layer from the response of the individual sensors of electronic nose, electronic tongue and the combined sensory response of electronic nose and electronic tongue. Layer (A) and Layer (B) are common to the fuzzy classifier model framework. Layer (C) is the Back propagation – multi layer perceptron (BP-MLP) neural network. It is used to realize the fuzzy rule automatically and it does not need prior knowledge about the fuzzy rule.
The artificial neural network has (m*t*n) input nodes, where, t is the number of transient response for individual m sensors in the multi-sensor array. It has been observed that there are four classes. Therefore, the output layer of the network needs to be assigned with four nodes, as shown in Fig. 2.
For simplicity, only one hidden layer has been considered which has H number of nodes. For the development of the artificial network of electronic nose, the value of m, t, n and H are 5, 66, 11 and 80 respectively. For the development of the artificial network of electronic tongue, the value of m, t, n and H are 5, 694, 11 and 850 respectively. For the combined sensory system again due to uneven data size obtained from electronic nose and electronic tongue Gaussian mean from each sensor response is taken, the value of m, n and H are 10, 11 and 5 respectively.

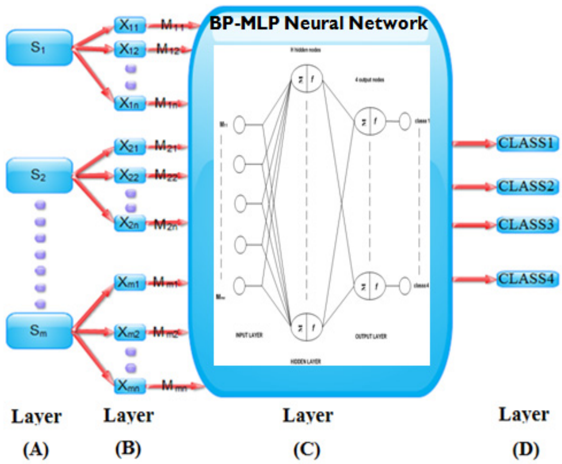
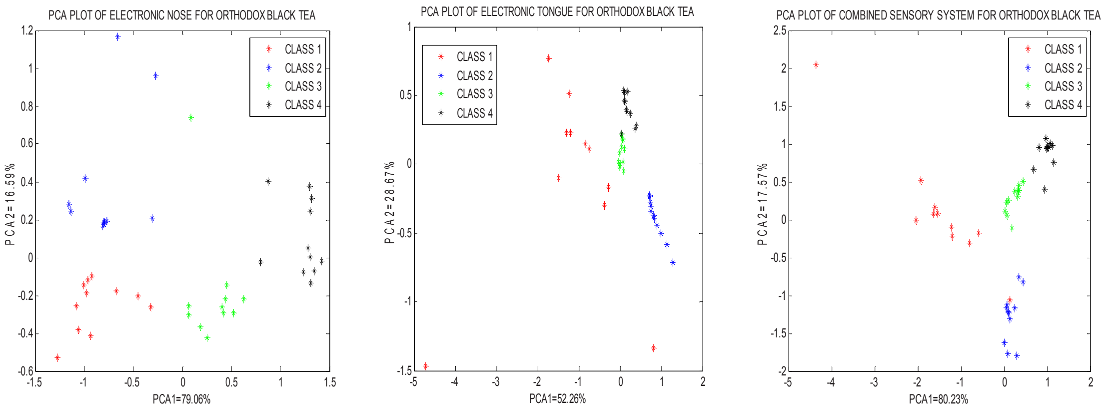


Fig. 4: Fuzzy Neural Network Architecture

The learning rate of the hidden layer is chosen as 0.001 and “logsig” is used as the activation function imposed on the hidden layer outputs. “tansig” has been used as the activation function of the output layer, and the learning rate in the output layer is taken as 0.01. Convergence during the learning process has been obtained with acceptable accuracy with only one hidden layer with H nodes.

4. Results and Discussions

Experimentations with electronic nose, electronic tongue and the combined sensory response of electronic nose and electronic tongue have been performed with 240 finished tea samples and sensor output signatures are logged in the computer. The whole data sets consist of four different types of tea grades. As a first step to identify underlying clusters in the electronic sensor signatures, the data obtained from each individual electronic sensor systems and the merged data are analyzed using principal component analysis (PCA) as shown in Fig. 5.



(a) (b) (c)

Fig. 5: PCA plot for 48 black tea samples of (a) electronic nose data (b) electronic tongue data (c) combined sensory response of electronic nose and electronic tongue data

The overall classification rate of all three classification techniques for individual sensory response of electronic nose and electronic tongue as well as its combined sensory response as shown in Table 1.

Table 1: Comparative results of separability index and mean classification rate between Fuzzy and FNN model for different sensory systems

Sensory system	Separability Index	Overall classification rate (in %)		
		Neural Network	Fuzzy	FNN
Electronic Nose	3.2294	73.021	74.612	75.417
Electronic Tongue	4.4493	76.667	79.381	81.498
Combination of electronic nose and electronic tongue	7.3003	78.375	87.259	89.442

From the Table 1, it is clear that the separability index and the classification rate have been increased for the combined sensory response of electronic nose and electronic tongue than individual sensory response. As stated in introduction that our first objective is to establish that combined sensor response is quite improved than individual sensor system. Secondly it is clear that among three types of classifiers FNN provides better classification rate than the neural network classifier and fuzzy classifier irrespective of the sensory system. Neural network requires large training data and since our dataset are not so large fuzzy is the better option and in fuzzy neural the drawbacks of both are minimised and more improved classification is obtained.

5. Conclusion

Neural networks provide self-organizing substrates for low level representation of information with on-line adaptation capabilities. Fuzzy logic is a very powerful tool for dealing quickly and efficiently with imprecision and nonlinearity. A fuzzy model is designed using Wang-Mendel Method for generating fuzzy IF-THEN rules from data and to make it a comprehensive and flexible fuzzy system approach. In this paper, we have also developed an intelligent classifier system, FNN classifier which provides the flavour to both neural network as well as fuzzy logic. Overall, the pattern classifiers described in this paper has all the desirable properties to have more acceptability in the tea industry and is expected to be extremely useful for standardization of electronic nose, electronic tongue and the combined sensory response of electronic nose and electronic tongue instrument for black tea classification.

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