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Quality Control of Coffee Using an Electronic Nose System

[1]Nidal F. Shilbayeh and [2]Mahmoud Z. Iskandarani
[1]Applied Science Department, Computer Science Department
P.O.Box 41, Post Code: 11931, Amman, Jordan
[2]Applied Science University, Computer Engineering Department
P.O.Box 911597, Post Code: 11191, Amman, Jordan

Abstract: An electronic nose system for quality control of coffee is designed and tested. The system uses the Figaro TGS800 series sensors with an integrated heating element. The testing of the system is carried out using different types of coffee where it is proved successful in classifying the tested coffees and actual discrimination of ingredients into different classes [10]. Database based software is designed to interface the built hardware and to process the electronic nose signals before being classified.

Key Words: Electronic Nose, Olfactory, Gas Sensor, Hardware, Software, Neural, Back-Propagation

INTRODUCTION

The standard approach to odor analysis is to employ a human sensory panel, which is a group of people with highly trained senses of smell. The disadvantages of human sensory panels include subjectivity, poor reproducibility (i.e., results fluctuate depending on time of day, health of the panel members, prior odors analyzed, fatigue, etc.), time consumption, and large labor expense. Also, human sensory panels cannot be used to assess hazardous odors, work in continuous production, or remote operation [1-7].

Analytical chemistry instruments such as gas chromatographs (GC) and mass spectrometers (MS) have been used to analyze both hazardous and non-hazardous odors. GC and GC/MS systems can require a significant amount of human intervention to perform the analysis and then relate the analysis to something useable.

The main motivation for electronic noses is the development of qualitative, low-cost, real-time, and portable methods to perform reliable, objective, and reproducible measures of volatile compounds and odors. In order to develop an electronic nose, it is useful to examine the physiology behind olfaction since biological olfactory systems contain many of the desired properties for electronic noses. Also, the contrast between an artificial system and physiology is necessary to achieve a reliable, subjective, and analytically acceptable system [11].

In this paper, a fully operational hardware/software system which models the function of the biological nose is presented and applied to coffee typed classification. The device is shown in Fig.1.

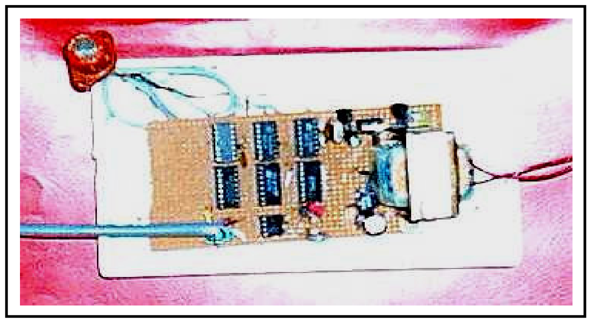

Fig. 1: The Designed Electronic Nose System

The Biological Nose: The mammalian olfactory system uses a variety of chemical sensors, known as olfactory receptors, combined with automated pattern recognition incorporated in the olfactory bulb and olfactory cortex in the brain [8, 9]. No one-receptor type alone identifies a specific odor. It is the collective set of receptors combined with pattern recognition that results in the detection and identification of each odor. Fig.2 illustrates the major components and function of the mammalian olfactory system and its sensory components. Odor molecules arrive at the olfactory receptors stimulating an electro-chemical response that is transmitted through the crib form plate to the olfactory bulb and ultimately the olfactory cortex.

The major operations olfaction can be broken into sniffing, reception, detection, recognition, and cleansing of odors. The olfaction process begins with sniffing, which brings odorant molecules from the outside world into the nose. With the aid of turbinated (bony structures in the nose which produce turbulence), sniffing also mixes the odorant molecules into a uniform concentration and delivers these molecules to the mucus layer lining the olfactory epithelium in the upper portion of the nasal cavity. Next, the odorant molecules dissolve in this thin mucus layer which then transports them to the cilia (hair like fibers) of the olfactory receptor neurons. The mucus layer also functions as a filter to remove larger particles.

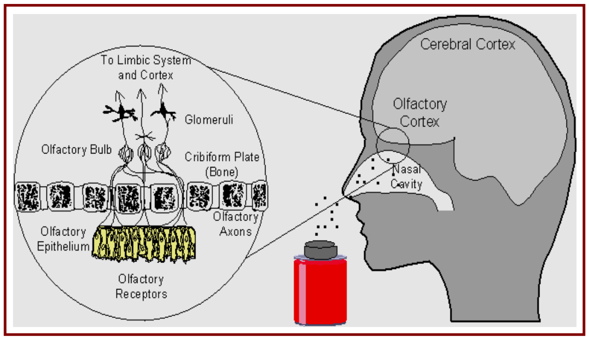

Fig. 2: Major Olfaction Sensing Components in Humans

Fig. 2; also illustrates the major components of the senses of olfaction and taste in the human. The major olfactory components are the olfactory receptors (sensors), the olfactory bulb (signal pre-processing), and the olfactory cortex (odor identification). The VNO is the vomero nasal organ and is associated with pheromone detection.

Reception involves binding the odorant molecules to the olfactory receptors. These olfactory receptors respond chemically with the odorant molecules. This process involves temporarily binding the odorant molecules to proteins that transport the molecules across the receptor membrane. Once across the boundary, the odorant molecules chemically stimulate the receptors. Receptors with different binding proteins are arranged randomly throughout the olfactory epithelium.

The chemical reaction in the receptors produces an electrical stimulus. These electrical signals from the receptor neurons are then transported by the olfactory axons through the crib form plate (a perforated bone that separates the cranial cavity from the nasal cavity within the skull) to the olfactory bulb (a structure in the brain located just above the nasal cavity). From the olfactory bulb, the receptor response information is transmitted to the olfactory cortex where odor recognition takes place. After this, the information is transmitted to the limbic system and cerebral cortex. There are no individual olfactory receptors or portions of the brain that recognize specific odors. It is the brain that associates the collection of olfactory signals with the odor.

Finally, in order for the nose to respond to new odors, the olfactory receptors must be cleansed. This involves breathing fresh air and the removal of odorant molecules from the olfactory receptors.

The Smart Electronic Nose System: The two main components of our system are the sensing system and the automated pattern recognition system as shown in Fig. 3. This combination of broadly tuned sensors coupled with sophisticated information processing makes the electronic nose a powerful instrument for odor analysis applications. The sensing system can be an array of chemical sensors where each sensor measures a different property of the sensed chemical, or it can be a single sensing device (e.g., gas chromatograph, spectrometer) that produces an array of measurements for each chemical, or it can be a hybrid of both. Each odorant or volatile compound presented to the sensor array produces a signature or characteristic pattern of the odorant [5,9 and 11].

By presenting many different odorants to the sensor array, a database of signatures is built up. This database of odorant signatures is then used to build the odor recognition system. The goal of this process is to train or configure the recognition system to produce unique classifications or clustering's of each odorant so that an automated identification can be implemented. Like biological systems, electronic noses are qualitative in nature and do not give precise concentrations. Unlike biological systems, current electronic noses are usually trained to identify only a few different odors or volatile compounds. Also, current systems lack the temporal dynamics found in biological systems and neuromorphic models. During operation, a chemical vapor or odor is blown over the sensor array, the sensor signals are digitized and fed into the computer, and the Artificial Neural Networks [3] (implemented in software) then identifies the chemical as shown in Fig. 4.

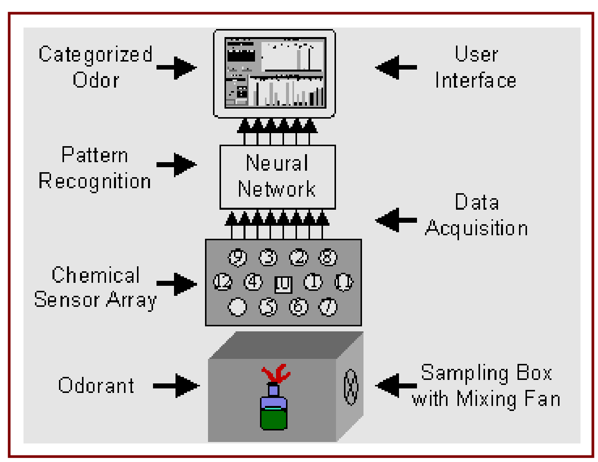

Fig. 3: Schematic of SENS

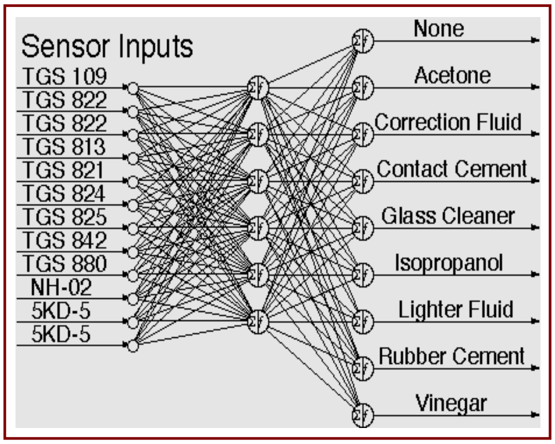

Fig. 4: Neural Networks Recognition Engine

System Hardware Design: The Smart Electronic Nose system is a system that converts the sensed odor in air to an electrical signal that is conditioned and sent to a computer to be interpreted and classified using a specifically designed Neural Network algorithms.

The main task of the designed hardware is to analyze the voltage response of the sensor after digitizing the signal using a level comparator. The digitized signal is then compared with the stored signals (odors signatures) for odor identification purpose.

The designed electronic nose comprises three main units as shown in Fig. 5.

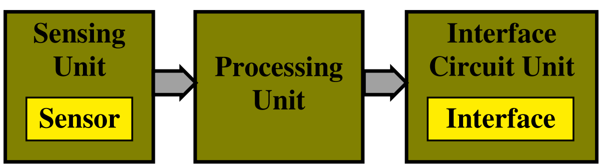

Fig. 5: System Block Diagram

Sensing Unit: The used sensing element is a Figaro gas sensor, which consists of a Tin Oxide (SnO_2) semiconductor [4], which has low conductivity in clean air. In the presence of a detectable gas, the sensor's conductivity increases depending on the gas concentration in the air. A simple electrical circuit can convert the change in conductivity to an output signal, which corresponds to the gas concentration. The used TGS 822 has high sensitivity to the vapors of organic solvents as well as other volatile vapors. It also has sensitivity to a variety of combustible gases such as carbon monoxide, making it a good general-purpose sensor. The sensor is also manufactured with a ceramic base which is highly resistant to severe environments with very high temperatures as shown in Fig. 6.

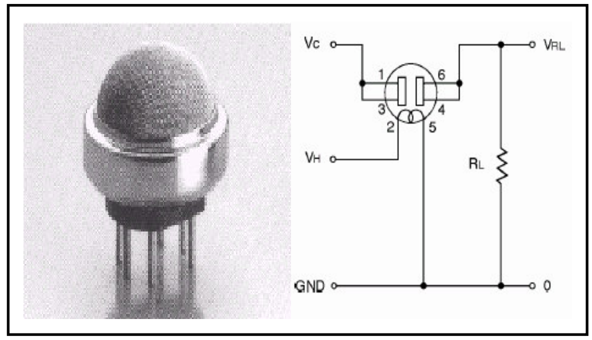

Fig. 6: Smell Sensor and its Equivalent Electrical Circuit

Processing unit: The main function of this unit is to digitize and condition the nose sensor signal as follows:

A clock signal is generated using the MC14060B 14-Bit Binary counter and oscillators shown in Fig. 7. The inverter in the circuit provides 180-degree phase shift for oscillation purposes, with the 1.5K Ohm resistors to provide the required negative feedback.

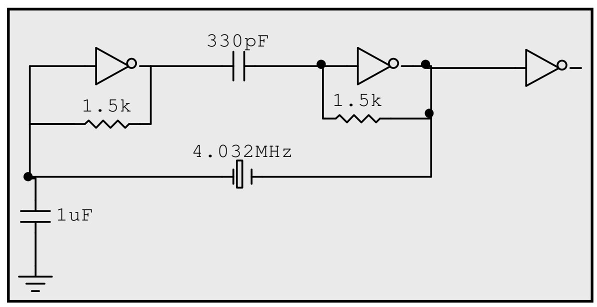

Fig. 7: Clock Generator

The frequency of the square wave, obtained from pin2 (Q13) of MC14060B device, can be calculated using the following expression:

$f = (4.032MHZ)/\sqrt{2^{13}} = 984.375HZ = 0.984KHz$, and a time constant can be obtained as $\tau = {}^{1}\!/_{f} = 1.016ms.$ as shown in Fig. 8 P (1).

The generated clock pulse signal is applied to the BC337/338 switching and latch circuit shown in Fig. 9. The common emitter transistor has capacitor connected to it and operates with the following characteristics:

1. Transistor is ON: signal at Q13 (MC14060B) is high; hence transistor output will be at level low.
2. Transistor is OFF: signal at Q13 (MC14060B) is low; hence transistor output will be at level high.

τ = RC= 6.8 k ohm* 0.22 uF= 1.496 ms.

Now, the transistor circuit output voltage can be calculated using the following formula:

$$V_c(T) = V_{cc}(1 - e^{(-t/\tau)})$$

$$V_c(T) = 5\text{ v}(1 - e^{(1.016\text{ms}/1.496\text{ms})}) = 2.5\text{ volts.}$$

The signal from the capacitor has a sawtooth shape with maximum amplitude of 2.5 volts. This signal is used as the reference signal on the Op-Amp which acts as a comparator as shown in Fig. 8 P(2). This comparator produces a signal resulting from the reference and nose sensor signal as shown in Fig. 11.

The sensor signal is obtained via a low pass filter and controlled by a variable resistor as shown in Fig. 10.

The obtained digital signal from the comparator (Fig. 8 P (4)) needs a time interval shift which is necessary to compensate for the zero value condition. This is achieved by inverting the Q13(MC14060B) signal and logically ANDing it with the comparator output signal as shown in Fig. 8 P(5).

The final stage of processing will be logically ANDing the time-shifted signal with a high clock signal Q14(MC14060B) as shown in Fig. 8 P(8). Now the signal is ready for the interface unit.

The interfacing unit receives the signal out of the AND gate and produces a digital count using the HEF4040B 12-stage binary counter. The output of the counter is multiplexed using the SN54/74LS151 8–input multiplexer. The output of the multiplexer form the input to the comparator as shown in Fig. 12.

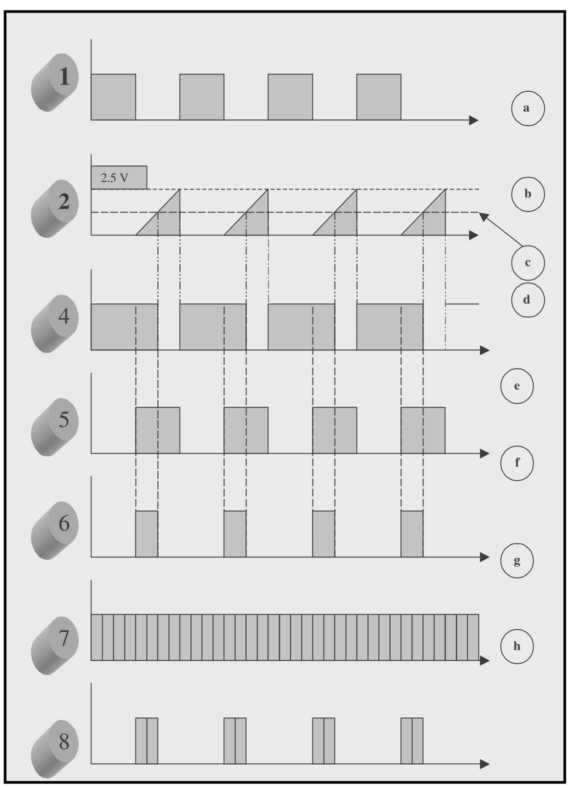

Fig. 8: Timing Diagram

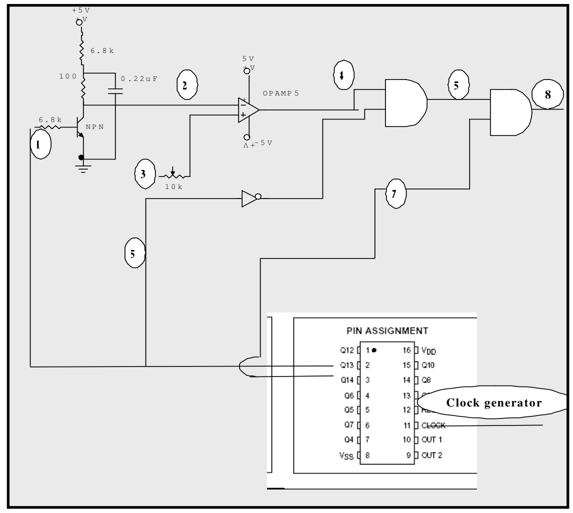

Fig. 9: Analog to Digital Converter

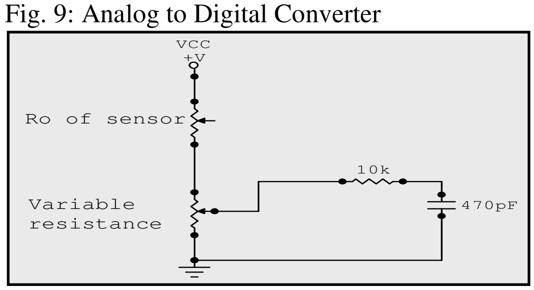

Fig. 10: Low Pass

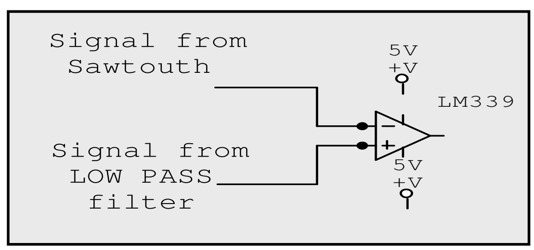

Fig. 11: Comparator Circuit

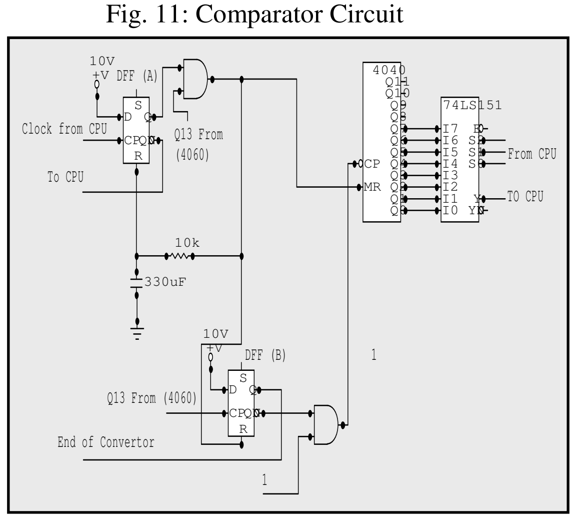

Fig. 12: Interface Unit

Software: The interfacing and processing software is programmed using visual basic 6.0. The electronic nose data is obtained via parallel port. The algorithm is shown in the flowchart in Fig.13.

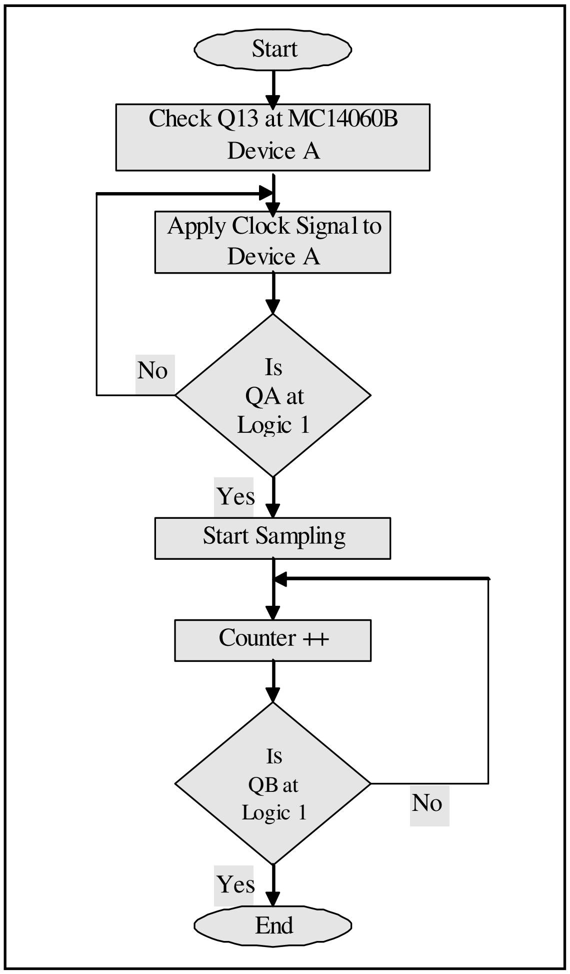

Fig. 13: Software Flowchart

RESULTS AND DISCUSSION

The basic factor used for discriminating between detected coffees is the average time of signal recovery of the Figaro sensor as shown in Table 1 and Fig. 14-16.

Table 1: Time Response of Coffee Mixtures

Time Min.)	Coffee 1	Coffee 2	Coffee 3
0	66	56	26
5	65	55	25
10	62	54	24
15	62	53	24
20	62	51	23
25	61	49	22
30	61	47	21

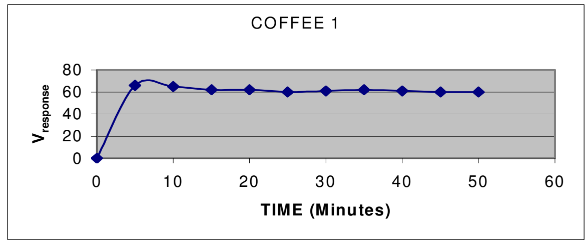

Fig. 14 : Coffee 1 Time Response

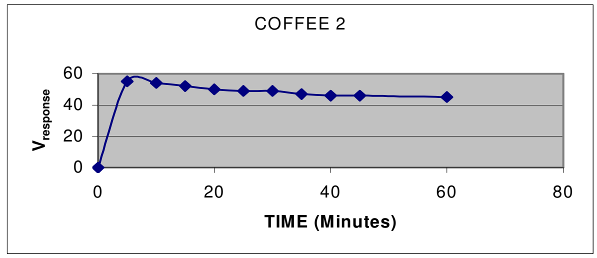

Fig. 15: Coffee 2 Time Response

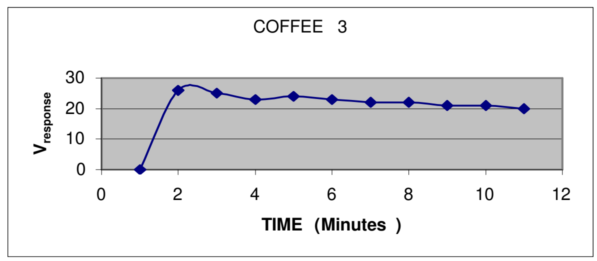

Fig. 16 : Coffee 3 Time Response

The tested coffee types which appear in Table 1 correspond to the following mixtures

1. Coffee 1: 2/3 black and 1/3 brown.
2. Coffee 2: 1/2 black and 1/2 brown.
3. Coffee 3: 1/3 black and 2/3 brown.

It is found that the time response (pulse count) corresponds to the percentage of mix of each type of coffee as follows:

A count of a 100% corresponds to a totally black coffee (heavily roasted beans). Now considering an interval of exposure of 5 minutes we realize the following:

i. A count of 65 corresponds to 2/3 black and 1/3 brown. Theoretically this type should have a response = 2/3 * 100 = 67. The difference between obtained value and calculated value is 67 – 65 =2. This represents an error in measurement and \ or inaccurate weight mix of beans or level of roasting.

ii. A count of 55 corresponds to ½ black and ½ brown. Theoretically this type should have a response = 1/2 * 100 = 50. The difference between obtained value and calculated value is 55-50=5.

iii. A count of 25 corresponds to 1/3 black and 1/3 brown. Theoretically this type should have a response = 1/3 * 100 = 33.3. The difference between obtained value and calculated value is 33-25=8.

From the previous we conclude the following:
1. The error is at minimum when the dominant type in the mix is black coffee as it carries the strongest smell.
2. The error is at maximum when the dominant type in the mix is brown coffee as it lightly roasted, hints it is aroma it not so strong.
3. The equally mixed has an error that lies in between the two values. This can be proved by taking the average of errors of 1 and 2. Which gives (2+8) / 2 = 5.

A neural network model is used to predict other levels of mixtures based on actual testing data[12]. The model is shown in Fig. 17. The network is trained using standard back propagation algorithm
This model is used to predict the mix type based on a given count value which can be used in quality control of coffee mixtures as shown in Fig. 18.

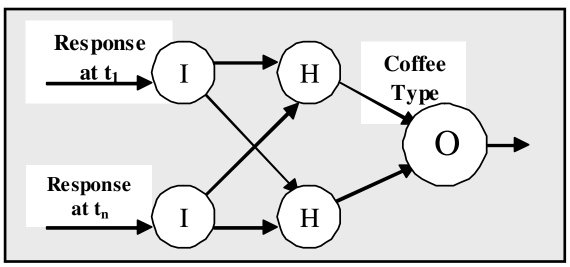

Fig. 17: Simplified Neural Network Model

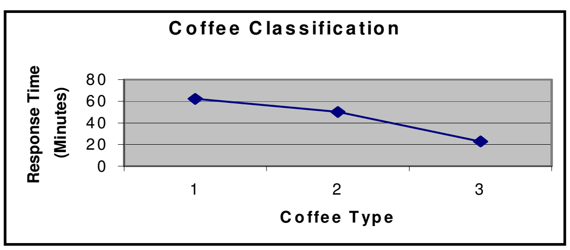

Fig. 18: Classification of Coffee Types

The designed smart engine that is used to analyze and classify signals generated by various herbs is based on the following principles:

1. Find the highest of all the input parameters
2. Normalize the obtained values and form an odor descriptor
3. Convert the normalized values to a digital code to be stored in the memory

Determination of how close an incoming herb odor pattern to a memorized one is carried out by the Neural part of the smart engine. Network of artificial neural elements are used. They have the ability to learn during a training process where they are presented with a sequence of stimuli inputs (herb odors) and a set of expected responses (signal amplitude). Learning is said to occur when the artificial neural engine arrives at a generalized solution for a class of odors (herbs). The system uses standard Back-Propagation algorithm in conjunction with a smart classification algorithm specifically designed to preprocess odor sensor signals.
Three coffee types were used to test the capability of both the designed electronic nose hardware and interpreting and classifying neural network software. Fig. 17 shows a simplified representation of the standard back propagation neural network model used for training, while Fig. 18 shows the system used for classification.
The designed software sampled the smell of each herb over a period of time described by the following expression

$$V_{response}(t) = V_{Sensor}(1- e^{(-t/\tau)})$$

This is carried out at 5 minutes intervals, which gives 7 samples per herb. These obtained samples are averaged in order to minimize any errors.
Table 1 shows a clear distinction between the three different types of herbs as classified by our system.
The system is capable of classifying large number of herbs with the ability to further increase its classification range and subclasses by using combination of sensors [12].

CONCLUSION

The designed and built TGS 800 series Smart Electronic Nose System proved to be an excellent system for the general purpose applications as it allows any of the 800 series sensors to be interfaced without the need for any hardware modification or adjustment. The initial choice of the TGS type of sensors is due to there simple design and the advantage of having an integrated heater which helps in stabilizing detecting element temperature and evaporation of adsorbed odors molecules, hence provides acceptable results that is improved through the use of hardware filtering and digitizing devices and an intelligent software which provides excellent classification. Further improvement could be introduced to our efficient system by integrating all sensors onto one device where by integration and miniaturization will improve the electrical characteristics of the sensing part of the designed system.

REFERENCES

1. Nagle H. T., 1998. The How and Why of Electronic Noses, IEEE Spectrum, pp. 22-33.
2. Staples, E. J., 1998. Dioxin/Furan Detection and Analysis Using a SAW-Based Electronic Nose, Proc. IEEE International Ultrasonic Symposium, Sendai, Japan.
3. Keller, P., 1994. Three Neural Network Based Sensor Systems for Environmental Monitoring, Proc. IEEE Electro 94 Conference, Boston.
4. Figaro sensors (www.figaro.com).
5. Deveza, R., D. Thiel, R.A. Russel, and A. Mackay Sim, 1994. Odor Sensing for robot guidance, The Int. J. Robotics Res., 13: 232-239.
6. Briem, G.J., J. A. Benediktsson and J. R., Sveinsson, 2001. Boosting, Bagging and Consensus Based Classification of Multisource Remote Sensing Data, In MCS, Cambridge, U.K, 2096: 279-288.
7. Gardner, and Bartlett, 1999. Electronic Noses, Oxford University Press.
8. Merler, S., C. Furlanello, B. Larcher and A. Sboner, 2001. Tuning Cost Sensitive Boosting and its Application to Melanoma Diagnosis, In MCS 2001, Cambridge, UK, 2096: 32-42.
9. Pardo, M. and G. Niederjaunfner, 2000. Data Preprocessing Enhances the Classification of Different Brands of Espresso Coffee with an Electronic Nose. Sensors & Actuators B, 69.
10. Vaid, T.P., M.C. Burl and N.S. Lewis, 2001. Comparison of the Performance of Different Discriminant Algorithms in Analytical Discrimination Tasks Using an Array of Carbon Black-Polymer Composite Vapor Detectors, Anal. Chem., 73: 321-331.
11. Shilbayeh, N. and M. Iskandarani, 2003. Discrimination of Perfumes Using an Electronic Nose System, WSEAS Trans. On Circuits and Systems, Issue 4, 2: 820-825.
12. Iskandarani, M. and N. Shilbayeh, 2004. “Hardware Design of a Smart Multi Purpose Electronic Nose System”, Asian J. Information Technology, Vol. 3 No. 10. (in press).