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Implementation of Electronic Nose using Neural Network

تطبيق الأنف الالكتروني باستخدام الشبكات العصبية

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ملخص البحث :

استخدمت الأنف الألكتروني في تطبيقات عدة لمجالات كثيرة بالحياة على سبيل المثال: صناعة الأغذية – حماية البيئة – التعرف على أنواع مختلفة من الغازات.

في هذا البحث تم التعرض لمشكلة التعرف على روائح جديدة لأنواع من الغازات مع مراعاة أن تصميم الأنف الألكتروني مبني على استخدام مجموعة من السنسور مع شبكة عصبية لأداء عملية التعرف النتائج التي تم الحصول عليها تبين أن نوع و تصميم الشبكة العصبية التي تم اختيارها تتعرف على الروائح الجديدة بدقة حوالي ٩٠.٤٨% تقريبا.

ABSTRACT

Electronic noses were engineered to mimic the mammalian olfactory system within an instrument designed to obtain repeatable measurements, allowing identifications and classifications while eliminating operator fatigue. They are used in several real-life applications such as food industry, environment protection, and gas identification. In this paper, an odor identification problem is addressed, where it is required to identify certain products according to their odors. An electronic nose is constructed using a number of sensors and a neural network to perform the identification. Experimental results showed that the proposed multilayer perceptron structure can identify new products with more than 90% accuracy.

Keywords: *Electronic* noses, Odor identification, Sensors, Neural Network.

I. Introduction

Electronic noses (EN), in the broadest meaning, are instruments that analyze gaseous mixtures for discriminating between different (but similar) mixtures, and in the case of simple mixtures, quantify the concentration of the constituents. 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 EN, it is useful to examine the physiology behind olfaction since biological olfactory systems contain many of the desired properties for ENs. Also, the contrast between an artificial system and physiology is necessary to achieve a reliable, subjective, and analytically acceptable system [1]. As shown in Figure 1 the main components of the EN, are typically consists of a multi-sensor array, an information processing unit such as an artificial neural network (ANN), software with digital pattern recognition algorithms, and reference-library databases. The output from individual sensors are collectively assembled and integrated to produce a distinct digital response pattern. Identification and classification of an analyte mixture is accomplished through recognition of this unique aroma signature (electronic fingerprint) of collective sensor responses. A reference library of digital aroma signature patterns for known samples is constructed prior to analysis of unknowns. The ANN is configured through a learning process (neural net training) using pattern recognition algorithms that look for differences between the patterns of all analyte types included in the reference library. This process continues until a previously selected level of discrimination is met. The results are validated and assembled into the reference library to which unknown

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samples can be compared. Identification of unknowns is based on the distribution of aroma attributes or elements that the analyte pattern has in common with patterns present in databases of the reference library [2].

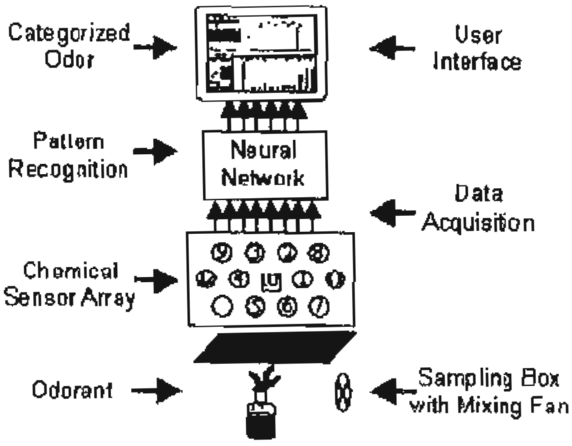

Figure 1: Schematic of an electronic nose [1]

Chemical sensors, which are the heart of the system, can be divided into three categories according to the type of sensitive material used: inorganic crystalline materials (e.g., semiconductors, as in MOSFET structures, and metal oxides); organic materials and polymers; and biologically derived materials [3].

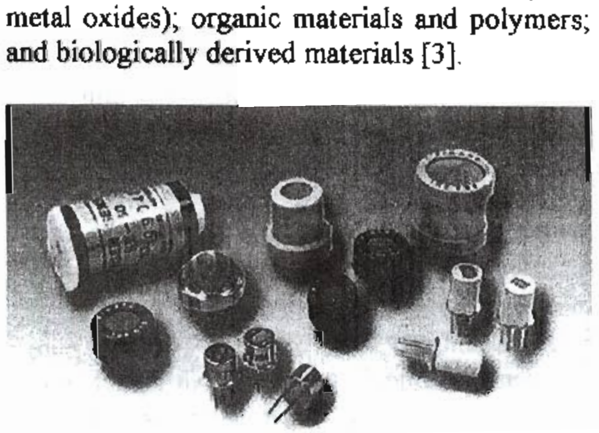

Figure 2: Types of transducer sensor [4]

Application areas for electronic nose:

The main application areas for ENs are food and environment [5-6-7]. More exciting are the possible medical applications where scientists are researching the use of EN to diagnose illness by smelling patients' breath with the possibility of installing tiny electronic noses in phone receivers, so that patients can simply breathe into the phone and wait for a diagnosis as shown in Figure 3 [8].

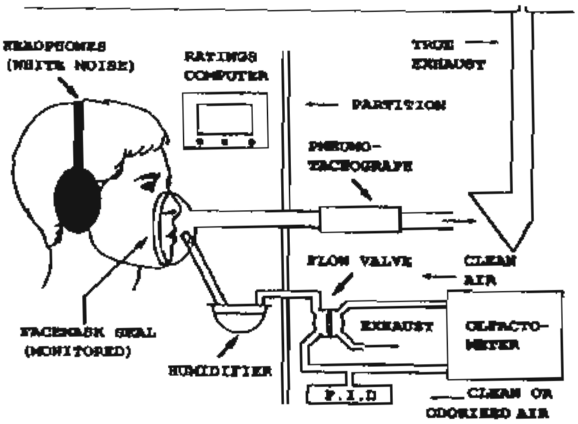

Figure 3: Schematic representation of the test station for measurement of sensory responses and breathing parameters in medical applications.

The combination of gas chromatography and mass spectroscopy (GC–MS) is by far the most popular technique for the identification of volatile compounds in foods and beverages. This is because the separation achieved by the gas chromatographic technique is complemented by the high sensitivity of mass spectroscopy and its ability to identify the molecules eluting from the column on the basis of their fragmentation patterns. GC and MS equipments are very complex and expensive therefore they are located in central medical or biochemical units so, physicians in remote places would have to send the samples to these units and wait for a number of days to receive the results. Comparatively, electronic noses are simpler, cheaper devices and the accompanying learning based intelligent system performs the whole process in less time [9].

Advantages of electronic nose:

Electronic noses do have significant advantages over human nose. Electronic noses do not get bored with repetitive smelling tasks, or de-sensitized through habituation to particular odors. Unpleasant smells such as industrial chemicals and sewage do not make electronic sniffers feel sick, and their performance on smelling tasks does not fluctuate according to mood, hormone cycles or other unpredictable human factors [10].

II. Problem Statement

Gas identification represents a big challenge for pattern recognition systems due to several particular problems such as non-selectivity and drift. The purpose of this paper is to introduce a classical pattern recognition algorithm for gas identification which models the function of the biological nose.

Where 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 [11-12]. No one-receptor type alone identifies a specific odor [1]. It is the collective set of receptors combined with pattern recognition that results in the detection and identification of each odor. So, our aim for this electronic nose is to respond to new odors, the way like biological nose.

In summary, the problem of interest to this work can be described as follows: Given a set of known odors, it is required to design an EN that can identify new odors.

III. Neural Network Solution

During operation, a chemical vapor or odor is blown over the sensor array, the sensor signals are digitized and fed into the computer. The identification is done by exploiting the ability of artificial neural network to "store information" about the given odors. Therefore, the artificial neural network as shown in Figure 4 (implemented in software) identifies the chemical based on the sensor readings where neural network transforms *n* inputs (sensor readings) to *m* outputs (odor classes).

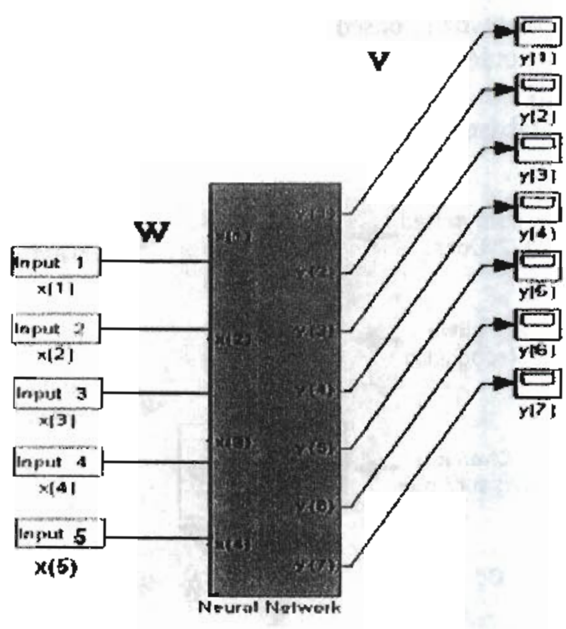

Figure 4: Neural Networks Recognition design

IV. Simulation & analysis

In this paper, we used the data already collected from five sensors exposed to 7 kinds of coffee using Pico-1 Electronic Nose [3]. Such sensors exhibit high sensitivity, lower power consumption, and compactness and compatibility with semiconductor technology. Our pattern recognition algorithms are MLP & RBF.

(a) Pico-1 Electronic Nose

Pico-1 Electronic nose as shown in Figure 5 consists of five semi-conductor, SnO_2 -based thin-films sensors were utilized. Two are pure SnO_2 sensors; one is catalyzed with gold, one with palladium, and one with platinum. A thin layer of noble metals was deposited as catalyst on three sensors to improve sensitivity and selectivity. Thin-film sensors produced by sputtering are comparatively *stable* and *sensitive*.

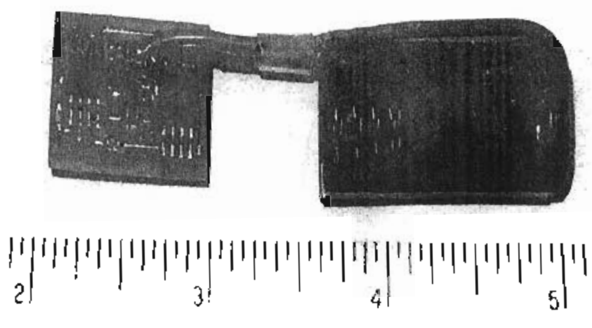

Figure 5: Pico-1 Electronic Nose design

The odor sampling system depends on the type of sample and on its preparation. For simple gas mixtures, one uses automated gas mixing stations consisting of certified gas bottles, switches and mass flow controllers [13]. In the case of complex odors like food odors, the volatile fraction (the so-called *headspace*) is formed inside a vial where a certain amount of odor-emitting sample is placed. The vapor can then be collected either by flushing a carrier inside the vial (*dynamic headspace scheme*) or extracted with a syringe and injected, at constant velocity, in the air flow which is used as carrier (*static headspace scheme*).

The electro-mechanical part of the EN used in this experiment consists of (see a scheme in Figure 6):

1) An auto sampler (Hs 850 CE Instruments). This device is a standard component of chromatographs; its utility is a high sample throughput and a high reproducibility due to the automation of the measurement process. It consists of a sample carousel, where the vials containing the odor-emitting sample are held, an oven, where the sample is pre-conditioned, and a movable mechanical arm with syringe (A).

2) A mass flow controller (B) to set the flow of the carrier gas.

3) A stainless steel chamber (C) which can contain up to five chemical sensors plus the humidity sensor.

4) Control electronics (D) permitting steering of the system (auto sampler, mass flow controllers, and sensors) via PC.

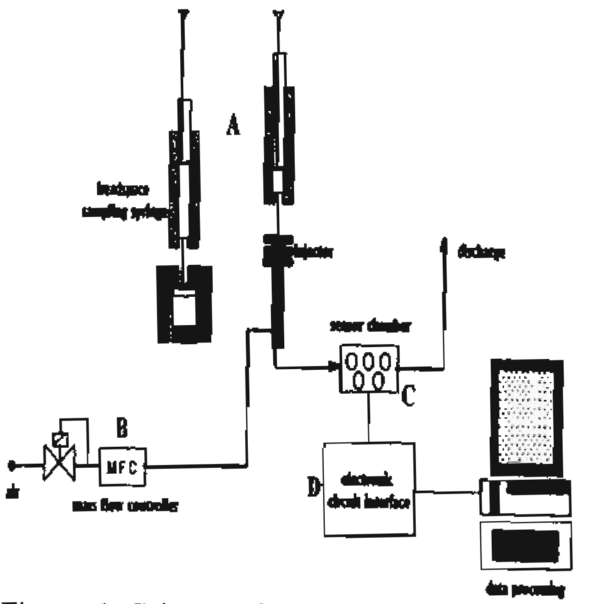

Figure 6: Scheme of the EN developed in the Gas Sensor Lab (static headspace sampling with syringe).

(b) Neural Network Analysis

The MLP which consists of number of neurons in each layer is as follows: 5 neurons in the input layer, 20 neurons in the hidden layer, and 7 neurons in the output layer and these layers are interconnected by weight matrices, W and V. Using the Matlab toolbox with the following design for MLP the neural network:

- Transfer function: tan sigmoid
- Training function: Levenberg-Marquardt back-propagation
- Learning rate: 0.9
- Number of epochs: 1500
- Number of maximum fail: 450

The weights of the MLP adjusted/trained using the gradient descent based back-propagation algorithm. The output layer neurons are formed by the inner products between the regression vector from the hidden layer and the output weight matrix.

During training the MLP starts with random initial values for the weights and then computes a one pass back-propagation algorithm at each time step k, which consists of a forward pass propagating the input vector through the network layer by layer, and a backward pass to update the weights by the gradient descent rule.

The RBF which consists with number of neurons in each layer is as follows: 5 neurons in the input layer, 20 neurons in the hidden layer, and 7 neurons in the output layer and these layers are interconnected by weight matrices, W and V. Using the Matlab toolbox version (7.6.0) with the following design for the RBF neural network:

- Transfer function: radial basis transfer function for the first layer & linear transfer function for the second layer
- Training function: Levenberg-Marquardt back-propagation
- Learning rate: 0.9
- Number of epochs: 1500
- Number of maximum fail: 450

In the RBF the first layer has radial basis neurons, and calculates its weighted inputs with distance and its net input with inner products. The second layer has linear neurons, and calculates its weighted input with dot product weight function and its net inputs with sum net input function.

Training is performed with the following repeated steps until the network's mean squared error falls below goal.

1. The network is simulated.
2. The input vector with the greatest error is found.
3. A radial basis neuron is added with weights equal to that vector.
4. The linear layer weights are redesigned to minimize error.

(c) Results & comparative analysis

Figure 7 illustrates the relation between mean squared error performance function of the MLP performance function for 156 epochs for the training, validation, and test performances given as a result the best validation performance was 0.018334 at epoch 56. Figure 8 illustrates the relation between the performance function of the RBF performance function for 175 epochs the best performance was 0.0183499 .When comparing with the previous work showed the classification rates were above 90% and our results after doing several trials are summarized in the table (I).

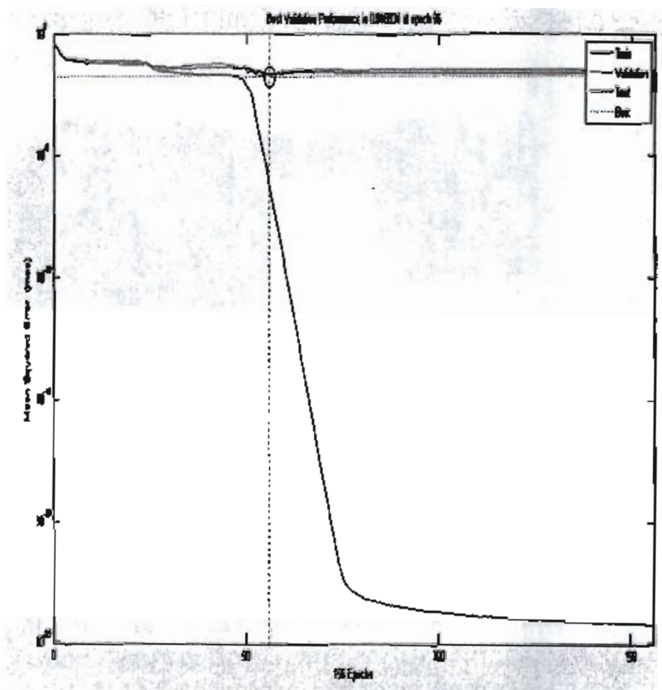

Figure 7: Performance curve of the MLP

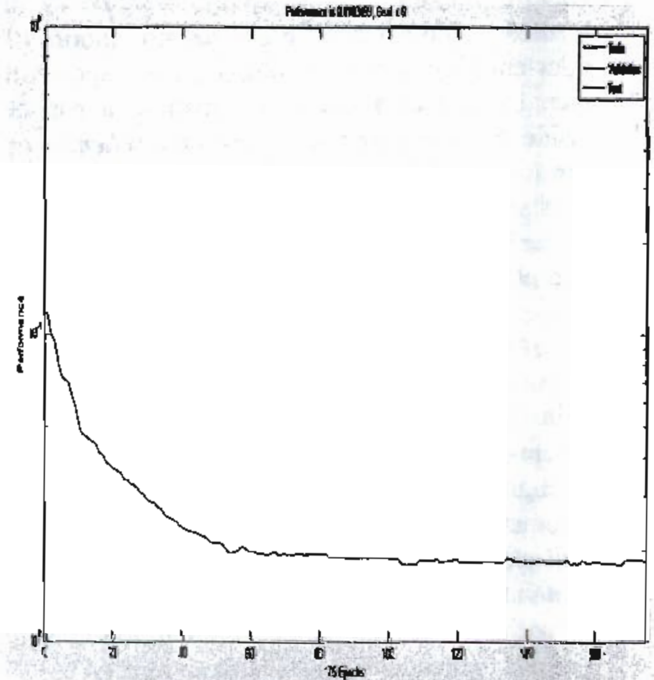

Figure 8: Performance curve of the RBF

Table (I): summary of last paper results

	Training performance	Test performance
MLP	**96.7742**	**90.4762**
RBF	**98.3871**	**85.7143**

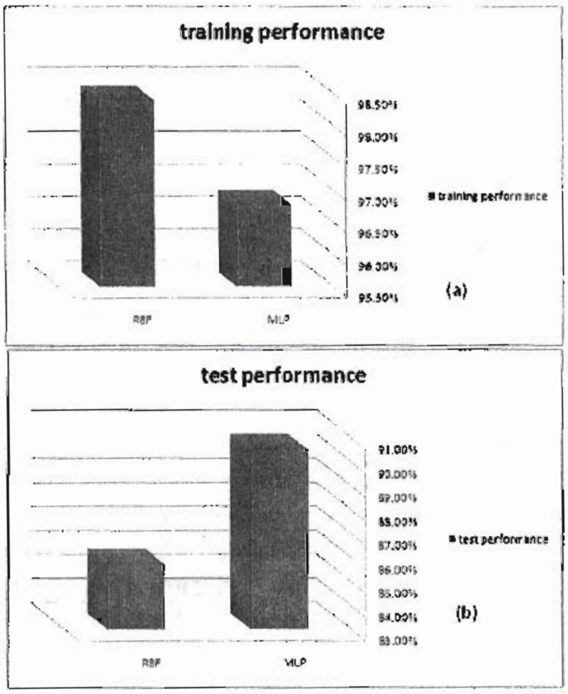

Figure 9: (a),(b) are the training & test performance percentages of the MLP&RBF .

V. Conclusion

In this paper, we presented an Electronic nose (EN), which is an instrument that analyzes gaseous mixtures to discriminate between different (but similar) mixtures and, in the case of simple mixtures, to quantify the concentration of the constituents. EN consists of a sampling system, a stable and sensitive array of chemical sensors, electronic circuitry, and data analysis software using the Matlab toolbox version (7.6.0) that permits reliably analyzing small datasets.

Our problem of interest in this work was to design a simple pattern recognition system that can identify new odors by using a given set of known odors this is done by using MLP that gives better results than RBF neural network.

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List of abbreviations

EN: Electronic Noses
ANN: Artificial Neural Network
MOSFET: Metal Oxide Semiconductor Field Effect Transistor
GC-MS: Gas Chromatography & Mass Spectroscopy
MLP: Multi Layer Perceptron
RBF: Radial Basis Function
PC: Personal Computer

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