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Sensor Characterization for Multisensor Odor-Discrimination System

A. del Cueto Belchi[1], N. Rothpfeffer[2], J. Pelegrí-Sebastia[1], J. Chilo[2], D. Garcia Rodriguez[1] and T. Sogorb[1]

[1]Department of Electronic Engineering, Polytechnic University of Valencia

C/ Paranimf, 1, 46730 Grau de Gandia (Valencia), Spain,

[2]Department of Electronics and Physics, University of Gävle SE-80176, Sweden

Email: jpelegri@eln.upv.es (corresponding author)

Abstract –In recent years, with the advent of new and cheaper sensors, the use of olfactory systems in homes, industries, and hospitals has a new start. Multisensor systems can improve the ability to distinguish between complex mixtures of volatile substances. To develop multisensor systems that are accurate and reliable, it is important to take into account the anomalies that may arise because of electronic instabilities, types of sensors, and air flow. In this approach, 32 metal oxide semiconductor sensors of 7 different types and operating at different temperatures have been used to develop a multisensor olfactory system. Each type of sensor has been characterized to select the most suitable temperature combinations. In addition, a prechamber has been designed to ensure a good air flow from the sample to the sensing area. The multisensor system has been tested with good results to perform multidimensional information detection of two fruits, based on obtaining sensor matrix data, extracting three features parameters from each sensor curve and using these parameters as the input to a pattern recognition system.

Keywords **–** multisensor, sensor characterization, prechamber, feature extraction, classification

I. INTRODUCTION

A very intensive research about olfactory systems is going on with the objective to find new alternative methods for volatile organic compound classification in different areas. Now, researchers can obtain large and heterogeneous signal datasets generated in real time. The data are then processed with complex algorithms to extract information that is useful for applications such as quality and taste determination, leakage detection, food and medical diagnostics. However, it is precisely in medical applications that olfactory systems are very interesting, and several research projects are under way. One reason for this is the several dog projects that run around the world for medical diagnosis [1-3]. If a dog can be used for these medical applications, why not use an electronic olfactory system that offers greater advantages?

Here, we briefly review the progress in the field of artificial olfaction for medical applications. In [4], the authors present a networked electronic nose, which can detect and recognize human odors from the armpit region. Studies of characterization of breath from smokers and nonsmokers using electronic nose were reported in [5] with the objective of proving the influence of smoking

on breath analyses. Moczko *et al.* present in [6] an optical diagnostic assay consisting of a mixture of environmental-sensitive fluorescent dyes combined with multivariate data analysis for quantitative and qualitative examination of biological and clinical samples using electronic nose and electronic tongue systems. Detection and diagnosis of lung cancer based on an electronic nose instrument that includes a gas extraction and capillary column to concentrate, desorb, and separate volatile organic compounds (VOCs) in patients' breath is found in a paper by Wang *et al.* [7]. References [8-9] aim to determine human blood glucose levels through analyzing the acetone present in exhaled breath as a noninvasive method with the help of an electronic nose system. Garcia-Cortes *et al.* propose in [10] a method to detect the presence of cortisol and adrenaline in body's sweat by electronic noses with resistive sensors as a noninvasive method. Finally, studies in [11] have shown the potential for early detection of microbial contaminants in urine samples using electronic nose technology.

A preliminary study of our work was presented in [12] where we use 32 gas sensors from Figaro Engineering Inc. to develop an olfactory system that can be used to classify a wide variety of volatile organic compounds. Some related applications that have been developed based on Figaro gas sensors are breath alcohol checkers, automatic cooking controls in microwave ovens, and air quality/ventilation control systems for home and automobiles. Figaro gas sensors are solid-state sensors composed of a sintered metal oxide that detects gases through an increase in electrical conductivity when reducing gases are adsorbed on the sensor's surface.

A simple electrical circuit shown in Fig. 1 can convert the change in conductivity to an output signal that corresponds to the gas concentration. The sensor requires two voltage inputs: heater voltage (V_{Heater}) and circuit voltage (V_{sensor}). The heater voltage (V_{Heater}) is applied to the integrated heater to maintain the sensing element at a specific temperature, which is optimal for sensing.

Circuit voltage (V_{sensor}) is applied to allow measurement of voltage (V_{out}) across a load resistor (R_L), which is connected in series with the sensor [13-14].

The ability to have different sensitivity properties by selecting the most appropriate combinations of the sensor temperature (V_{Heater}) and the possibility that Figaro Engineering Inc. provides various types of sensors enables the development of a multisensor olfactory system with 32, 64, 128, or more sensors.

Thereafter, the output signals from the sensors are digitized and stored for each sample. In this work three features parameters are extracted from each sensor curve: transient slope, saturation slope and maximum slope. These parameters are used as the input to a pattern recognition system to classify the substance under test.

II. OLFACTORY SYSTEM

A. Sensor Characterization

The basic assumption behind our olfactory system is that normal variations in the MOS sensors from Figaro Engineering Inc. combined with the selected operating temperature lead to a wide range of different responses toward volatile organic compounds. We have used seven commercial MOS that are sensitive to various types of gases: TGS2610-C00, TGS2610-D00, TGS2611-C00, TGS2600-B00, TGS2620-C00, TGS2602-B00, and TGS2442-B02. Because of the high sensitivity of these sensors, they are used in residential gas alarms, gas leak checkers, indoor air quality controls, and residential CO detectors. Subsequently, these sensors can be beneficially used in more complex applications, such as in medicine to detect various diseases, particularly different types of cancers.

Figaro sensors require a small amount of power to operate the sensor element at elevated temperatures between 200˚C to 400˚C. By varying the operating temperature, changing V_{Heater}, we can alter the sensor's response to various combustible gases. The seven types of sensors used in this work were investigated with the measurement setup illustrated in Fig. 2 to determine their V_{Heater} range.

The sensor characterization system is based on a virtual instrumentation system, where two instruments are connected to a computer via GPIB bus, and the LabVIEW is used to handle them. A power source (FA-851) supplies two drive currents, one for the sensor (Rs) and the other for the heater (Rh). Then, a digital multimeter (HP 33120A) is used to measure the output voltage of the sensor on the load resistor (R_L). Table I lists the range results in the form of current instead of voltage for some sensors.

B. System Design

The complete system is shown in Fig. 3 consisting of two parts: the electrical part and the part of the preprocessing of the samples, the prechamber. The electrical design of the system consists of eight identical electronic boards with four sensors in each of them. Each board includes a voltage regulator (LP38692MP-ADJ), which supplies the heater (V_{Heater}) for each of the four sensors. This regulator is controlled by the user interface and allows us to vary the supply voltage during the measurement process. The output voltage (V_{out}) of each sensor is fed into an amplifier (OP074) in a voltage follower configuration.

For data acquisition, we use an ADC from the National Instruments (NI USB-6218, 16 Bits, 250 kS/s, Isolated M. Series MIO DAQ, Bus-Powered). The NI USB-6218 has 32 analog inputs that we use for data collection from the 32 sensors and only two analog outputs that are used to

adjust the output voltage of the regulator and to control the electrovalve. In addition, it has 32 digital I/O lines that can be used to control some functions of the system by software.

The first part of the prechamber has a clean air pump. The air flow is adjusted manually with a small valve. This air is split into two streams, one that goes through the sample chamber and thereafter to the electrovalve and the other that goes directly to the electrovalve. The electrovalve is controlled automatically from the interface. The process is as follows: clean air passes through the system to clean it during a predetermined time and then passes air flow through the sample chamber during another fixed time.

The setup of the parameter for the measurements is controlled by a dedicated graphical user interface (GUI) implemented using LabVIEW on a personal computer [15]. This highly GUI allows to configure the hardware with full control and flexibility.

From the GUI, we can configure individually each sensor. Figure 4 shows the configuration panel in different colors corresponding to the eight electrical boards.

III. DATA ANALYSIS

For classification, the analysis process involves presenting the multisensor measurements to the input of a classification machine for a given slice of time. However, the raw data can be quite large and/or noisy to be effective, so a preprocessing step is needed to reduce the raw data to a smaller input data set that highlights particular features in the signals. In our case, data preprocessing is done using the software functions from LabVIEW. For example, we have designed an IIR low-pass digital filter of second order with variable cutoff frequency to eliminate any possible ripple.

The measurement steps used in our system are presented in Fig. 5. The first step in the olfactory analysis is to present a reference gas (clean air) to the sensor to obtain a reference line. Then the sensor is exposed to an odoriferous substance, causing changes in its output until the sensor reach a steady state. Finally, the odorant is flushed out of the sensor using the reference gas, and the sensor returns to its original state. From the software, we can set the open, acquisition, and close times depending on the substance to be analyzed.

The classification features used in our system are presented in Fig. 6 and are late saturation, saturation slope, early saturation, transient slope, and time to threshold [16-17].

The system has been tested with a number of substances working well. The analysis presented here is on the response of two fruits: pear and apple. Ten samples of every one. The output of the sensors consists of 32 independent analog voltages, each varying with time and odor. The voltage is sampled at 100 samples/second, and the raw data file is compacted to a data matrix consisting of 32 columns by 2000 rows.

As in previous works [18], the sampled signals are reduced to three numbers for each sensor: transient slope, saturation slope, and late saturation—three features that are believed to describe the origin of the signals well.

Pattern recognition algorithms are necessary to extract useful information from sensor outputs. One of the most common pattern recognition techniques used is principal component analysis (PCA) [19-20]. PCA is a linear data reduction technique, which reduces multivariate data into two or three dimensions. This technique extracts features by projecting the high-dimensional data set into a dimensionally reduced space formed by the uncorrelated and orthogonal eigenvectors of the covariance matrix calculated from the sensor responses, called principal components. The magnitude of the single eigenvector or percentage of information is expressed by the eigenvalue, which gives a measure of the variance related to that principal component [21].

This work uses PCA to visualize the similarities and differences between the various measurements in the dataset, using the first feature, transient slope. Fig. 7 shows the result plot of data in the PC1-PC2-PC3 plane of pear and apple. It is shown that the measurements are divided into two different groups.

The primary data are the 32 signals from the sensors (different sensors operating at different temperatures each) which are digitized and stored for each sample. Three features parameters are extracted from each sensor curve (transient slope (TS), saturation slope (SS) and maximum slope (MS) when the sample is closed), making a total of 96 parameters for each sample. Those parameters are used as the input to the pattern recognition systems: WEKA [22]. This is an open source data mining toolbox (written in Java) developed by Ian Witten's group at the University of Waikato. It provides tools for all the tasks usually performed in data mining, including numerous algorithms for pre-processing, classification, regression and clustering. Here we utilized 10 different classification algorithms in WEKA. We used their default parameters unless otherwise stated.

Here are the classification algorithms used in our work with their default parameters unless otherwise stated:

- **BayesNet** creates a Bayesian Network with implementation of the standard naïve Bayes algorithm, where normal distribution is for numerical features.
- **RBFNetwork** is an implementation of radial basis functions.
- **SimpleLogistic** constructs linear logistic regression models.
- **SMO** is a sequential minimum optimization algorithm for building support vector machine.

- **IB1** is a nearest-neighbor algorithm that classifies an instance according to the nearest neighbor identified by the Euclidean distance.
- The **Kstar** algorithm uses entropic distance measure, based on the probability of transforming one instance into another by randomly choosing between all possible transformations, and turns out to be better than Euclidean distance for classification.
- **VFI** finds intervals for each feature and attributes each class according to the number of instances with the class in the training set for the specific interval. Voting is used to select the final class for an instance.
- **ADTree** algorithms create trees as models.
- **NNge** is a nearest-neighbor algorithm that learns rules based on the hyper rectangles that it divides the instance space.
- **PART** constructs rules based on partial decision treesOur inexhaustible power source supplies.

Table II gives the results for 20 runs (10 pears and 10 apples) from our experiment.

V. CONCLUSION

This work has used 32 gas sensors (seven different types of sensors) from Figaro Engineering Inc. to develop an olfactory system that can be used to classify a wide variety of volatile organic compounds. A wide range of responses can be obtained by selecting the most appropriate combinations of the sensor working temperature. To know the most suitable temperature combinations, we have characterized each sensor.

The olfactory system has been verified with tests of two fruits, pear and apple, and classification algorithms such as PCA and others found in WEKA with good results.

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Figure and Table Captions

Figure. 1. Basic measuring circuit.

Figure 2. Sensor characterization setup.

Figure 3. The complete system: electrical design of the system and the prechamber.

Figure 4. Sensor configuration panel.

Figure 5. Measurement steps.

Figure 6. Classification features.

Figure 7. PCA using Transient Slope.

TABLE I.RANGE OF SENSOR TEMPERATURES

TABLE II.CLASSIFICATION RESULTS WITH WEKA

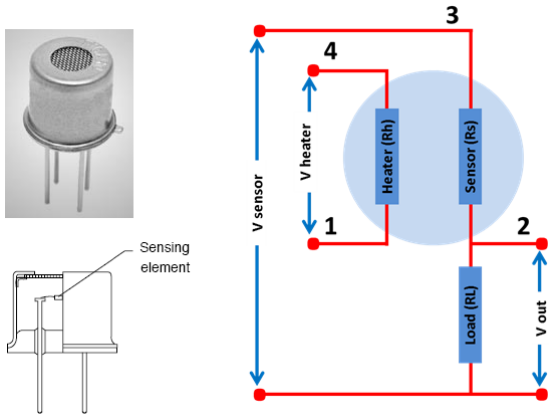

Figure 1. Basic measuring circuit

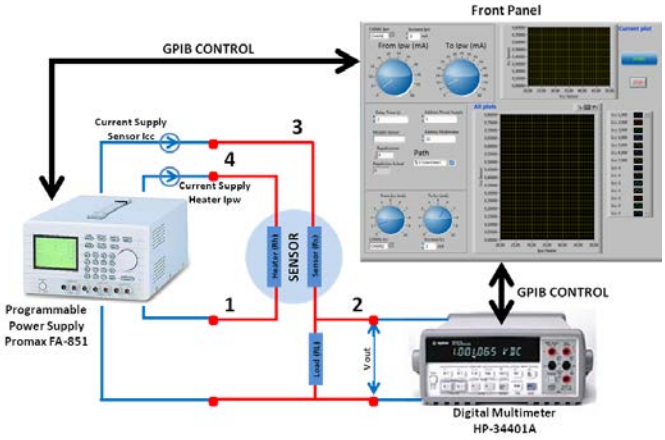

Figure 2. Sensor characterization setup

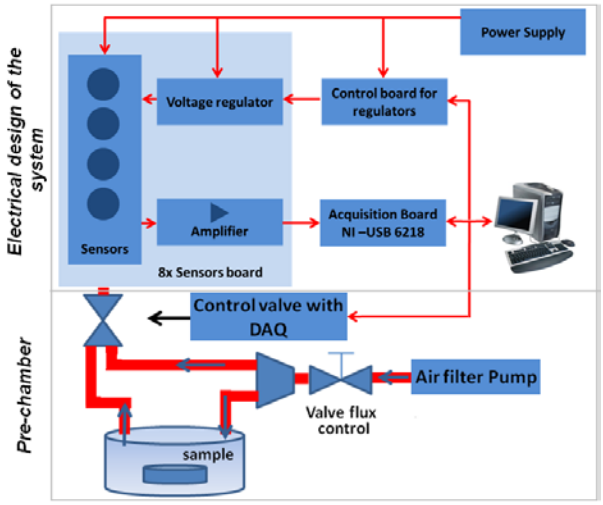

Figure 3. The complete system: electrical design of the system and the prechamber

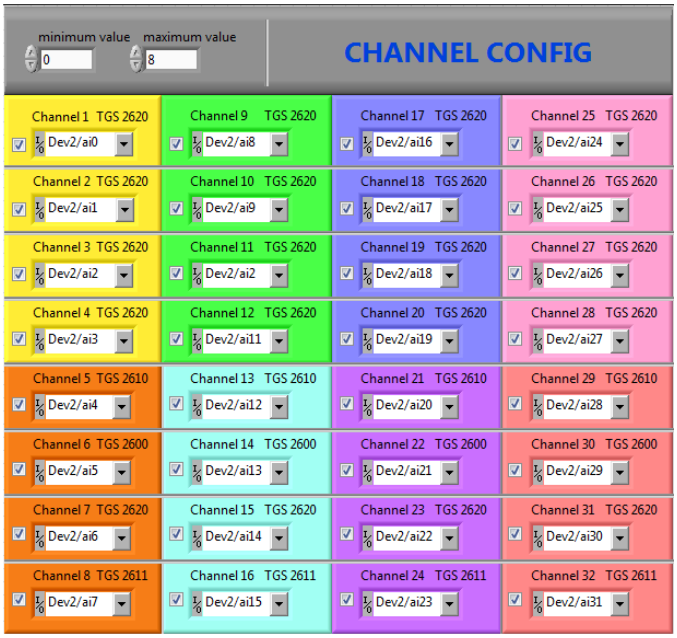

Figure 4. Sensor configuration panel

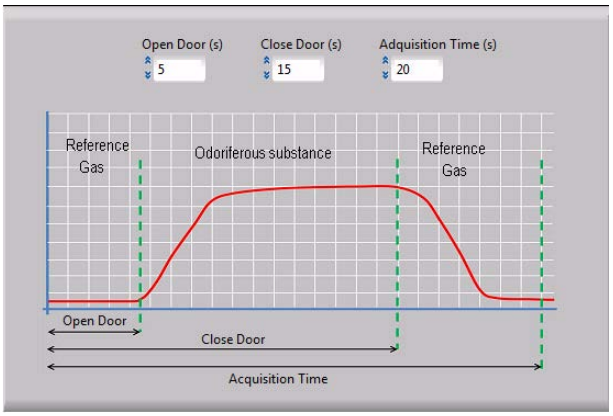

Figure 5. Measurement steps

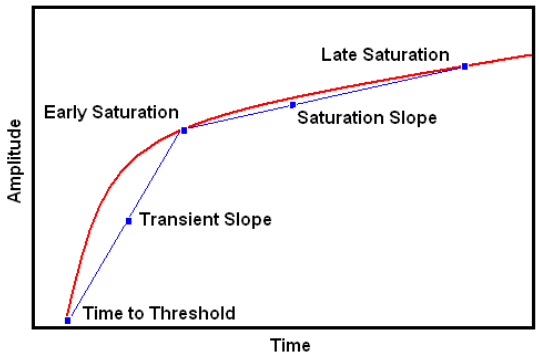

Figure 6. Classification features

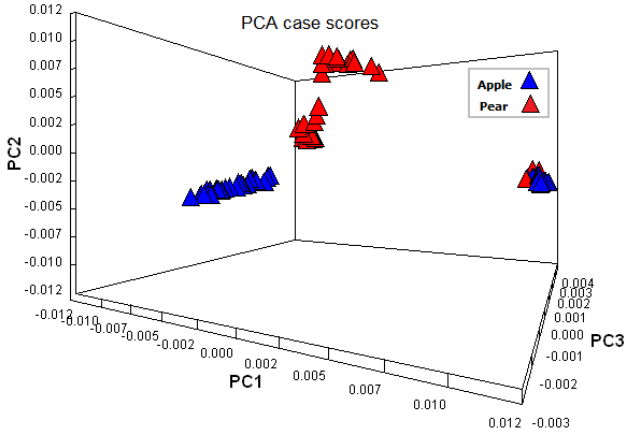

Figure 7. PCA using Transient Slope

TABLE I. RANGE OF SENSOR TEMPERATURES

Sensor	**Isensor (mA)**	**IHeater (mA)**
TGS2600	2.5-6.0	30-38
TGS2602	3.0-6.0	35-45
TGS2610-C00	2.5-6.0	30-45
TGS2610-D00	2.5-6.0	30-45
TGS2611	2.5-6.0	30-38
TGS2620	2.0-6.0	25-35
TGS2442	NC*	NC*

* Not Characterized due it uses different circuit diagram

TABLE II. CLASSIFICATION RESULTS WITH WEKA 40 SAMPLES

Classification Algorithm	Pear	Apple	Total (%) Correctly Classified
Bayes Network	37/39	38/40	94
RBF Network	38/39	36/40	93
SimpleLogistic	39/39	38/40	97
SMO	39/39	39/40	99
IB1	39/39	40/40	100
KStar	39/39	38/40	97
VFI	34/39	36/40	89
ADTree	39/39	36/40	95
NNge	39/39	38/40	97
PART	38/39	36/40	94