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E-nose development for safety monitoring applications in refinery environment

C. Pace[a], W. Khalaf[b], M. Latino[c], N. Donato[d], G. Neri[5] *

[a]*Dept. of Electronics Informatics and Systemistics, Università della Calabria, Cosenza, Italy.*
[b]*Dept. of Computer and Software Engineering, University of Almustansiriya, Baghdad, Iraq.*
[c]*Dept. of Chemical Science and Technologies, University of Roma Tor Vergata, Roma, Italy.*
[d]*Dept. of Matter Physics and Electronic Engineering, University of Messina, Messina, Italy.*
[e]*Dept. of Industrial Chemistry and Materials Engineering, University of Messina, Messina, Italy.*

Abstract

The E-nose system reported is designed to address the problem of early and distributed detection of dangerous gas mixtures. It is made of a selection of Commercial Off-The-Shelf (COTS) sensors, facing a small volume chamber, whose signals are conditioned and sampled by a multifunction board connected to a personal computer. A program, implementing efficient Support Vector Machine and least square model algorithms, executes the gas classification, the concentration estimation and warns about set risk thresholds overcoming. The system training was performed in laboratory, over a wide range of concentrations in air of: methane, hexane, pentane, and hydrogen sulfide. Other boundary conditions, such as oxygen concentration, temperature and RH are also taken into account. The overall cost of the system can be made very low, adopting an embedded architecture approach, allowing to overcome the limitations of the monitoring systems deployment inside refinery plants due to the high costs of traditional GC systems.

Keywords: Electronic Nose, Support Vector machine, Safety Monitoring

1. Introduction

The early and distributed detection of dangerous gas mixtures is a serious task in many industrial plants, especially in oil refineries where a great amount of hydrocarbons, volatile organic compounds and toxic gases, like hydrogen sulfide, are unavoidably emitted. Their presence, depending on mixture concentration values, can expose the workers to poisoning and explosion risks. The authors are

* Corresponding author. Tel.: +39-090-397-7297; fax: +39-090-397-7468.
E-mail address: gneri@unime.it.

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experienced on development and characterization of gas sensors [1] and in the development of pattern recognition and modeling algorithms [2,3], then, starting from a specific request from the Midland oil Company refinery of Aldora, Baghdad, Iraq, and considering the lack of low-cost instrumentation suitable for the purpose, they designed and validated the e-nose here reported.

2. Experiments

The schematic diagram of the developed sensing system is reported in Fig.1. To achieve good recognition performances, several sensors with different selectivity patterns are used and pattern recognition techniques was implemented in order to overcome the poor selectivity of each individual sensor [2,4].

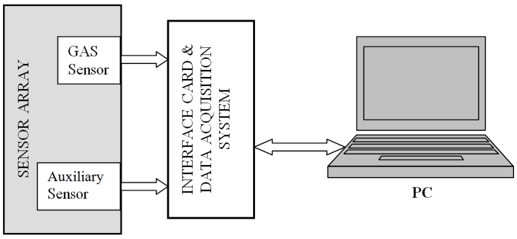
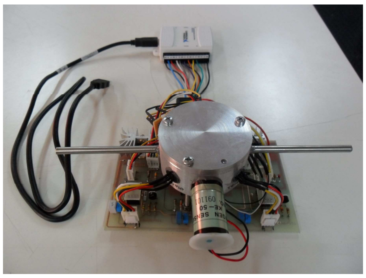
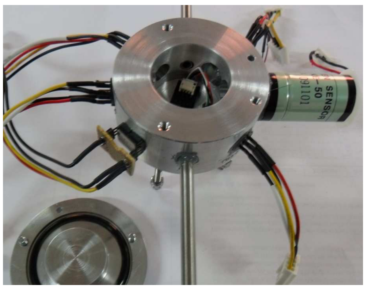


Fig 1: Block diagram of the proposed system.

The developed system consists of five sensors, from FIGARO USA INC. Two of them are semiconductor type (TGS-825, TGS-2611), the other two are catalytic type (TGS-6810, TGS-6812), plus an electrochemical oxygen sensor (KE-50). In addition, since environmental changes have a strong effect on most sensors, two more devices was integrated: a temperature and humidity sensor (HTG-3535 from Measurement Specialties), and a pressure sensor (XFAM from Fujikura Ltd.). The gas sensors are installed in a custom designed chamber (Fig.2.a.). An electronic board has been designed in order to optimize power supply and signal conditioning of the sensors. The signals are routed to an USB multifunction board (NI DAQ-6008 from National Instruments) and the acquisition and data analysis software was developed in LabWindows/CVI^{TM} environment.



(a)



(b)

Fig 2: (a) The e-nose system hardware, showing the inlet and outlet ducts for the constant mixture flux training phase that is made in laboratory. (b) Sensor chamber (around 30 cm^3) used in the unplugged position during the testing phase.

The training data are acquired by feeding the e-nose, with the cap in place, with a constant mixture flux by means of a laboratory gas control system. This apparatus is able to handle both gas bottles and permeation tubes, in order to generate a wide gas concentration range in a repeatable and reliable way. In testing phase, the chamber is open (Fig.2.b.) and the system makes use of the training parameters obtained by minimizing the leave-one-out cross validation error over the training set to find out the gas type. It also uses the least square approach, but this time for regression, to estimate the concentration. In Table 1 are reported the gas concentration values employed in the training procedure, the gas mixtures were further humidified to change relative humidity values, in order to evaluate the humidity effect in the sensor response.

Table 1. Training phase experiments performed using a constant flux laboratory gas control system.

Gas Name	Concentration Range (ppm)	No. of Samples
Methane	0 – 8000	8
Hexane	0 – 10000	10
Pentane	0 – 12000	6
H_2S	0 – 20	8
Oxygen	0% - 100%	6

3. Results

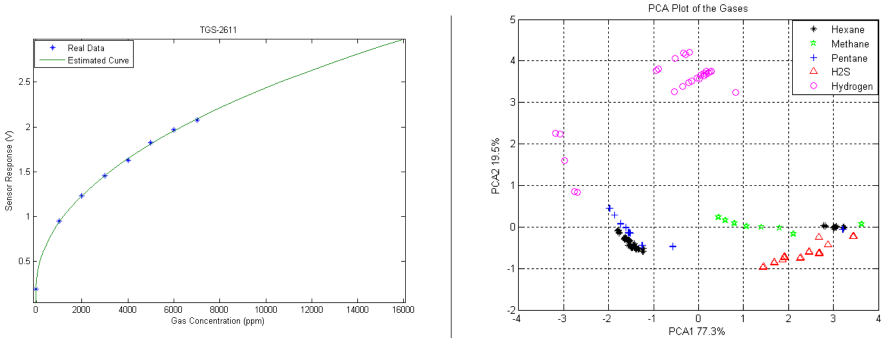
In the first analysis, we used a SVM with linear kernel, and we applied a multi-class classification by using the LIBSVM-2.82 package. The optimal regularization parameter C was tuned experimentally by minimizing the leave-one-out cross-validation error over the training set. Each classifier was trained on the 38-sample training set. Additionally, for the SVM classifiers, extensive cross-validation (CV) analysis was done to search for an effective combination of parameters. The standard randomized 10-fold cross-validation (R^8-CV), in which the data was randomly divided into ten groups, one of which was left out and used as the cross-validation set on each iteration. As a consequence, for consistency the results presented below all use classifiers evaluated with R^8-CV.

The classification results for each of the tested classifiers resulted in 100% cross-validation accuracy.

Once the classification process has been completed, the next step is to estimate the concentration of the classified analyte. To this aim, we use the least square regression approach. We build a polynomial model of the response (sensor signal versus analyte concentration) for each sensor and each analyte. Then we use this approximation to find the concentration for each analyte type. For the two semiconductor type sensors (TGS-825, TGS-2611), the concentration dependence of the response to a single analyte exposure can be described by a 3° degree polynomial, while for the catalytic type sensors (TGS6810, TGS6812) a model of 2° degree polynomial is enough. As an example, Fig. 3.a shows the estimated response to Methane for the TGS2611 sensor. The optimal estimate of the concentration is, in our model, a combination of the outputs of the diverse sensors. We have adopted the least square regression model to find the optimal weights on the basis of the experimental data. We come out in our experiments with four measures for each analyte sample. The weights α's are obtained by solving the following minimization problem :

$$\min_{\alpha_1 \ldots \alpha_m} \sum_{l=1}^{n} (\overline{c^{(l)}} - \sum_{i=1}^{M} \alpha_i c_i^{(l)})^2 \qquad (1)$$

where n is the number of analyte samples, $\bar{c}$ is the true concentration, M is the number of sensors (in our case M = 5), c is the concentrations that have been previously calculated.



(a) (b)

Fig. 3. (a) Estimated response to Methane for the TGS2611 sensor.(b) PCA plot; The data set for these gases is made up of samples in R8 space where each sample corresponds to the outputs of the sensors for a given couple (gas, concentration).

For the Methane case, with the sensor TGS2611, we obtained the following results:

Table 2. Results of the suggested regression model .

Real Concentration (ppm)	Estimated Concentration (ppm)	Relative Error (%)
1000	1029	2,90
2000	1991	0,45
3000	2986	0,47
4000	3905	2,38
5000	5092	1,84
6000	6078	1,30
7000	6921	1,13

The PCA plot of the training phase is reported in Fig.3.b. Preliminary application in the refinery environment demonstrated the functionality of the system.

4. Conclusions

In this paper is reported the development and validation of an e-nose system for refinery environments based on commercial sensors. The system has been preliminary tested in a real refinery environment and generated interest as an innovative system that can potentially lead, thanks to its low-cost approach, to a wide-area monitoring of dangerous situations.

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