Multisensor system for toxic gases detection generated on indoor environments

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Abstract. This work describes a wireless multisensory system for different toxic gases detection generated on indoor environments (i.e., Underground coal mines, etc.). The artificial multisensory system proposed in this study was developed through a set of six chemical gas sensors (MQ) of low cost with overlapping sensitivities to detect hazardous gases in the air. A statistical parameter was implemented to the data set and two pattern recognition methods such as Principal Component Analysis (PCA) and Discriminant Function Analysis (DFA) were used for feature selection. The toxic gases categories were classified with a Probabilistic Neural Network (PNN) in order to validate the results previously obtained. The tests were carried out to verify feasibility of the application through a wireless communication model which allowed to monitor and store the information of the sensor signals for the appropriate analysis. The success rate in the measures discrimination was 100 %, using an artificial neural network where leave-one-out was used as cross validation method.

1. Introduction
Nowadays wireless communication systems for different industrial applications have important advantages (compared to the conventional wiring), since they tend to increase the efficiency and safety in each of the processes. One of the main advantages that provide these types of systems is low cost of installation and maintenance [1]. Most of the Industrial facilities are rigorous and expensive because they are demanding in terms of quality of cabling requirements. Therefore, less cables means to use fewer elements in the system, especially when it comes to modernizing or upgrading components within the industry. For this reason, a wireless communication system coupled with an electronic nose can be a solution to be implemented in environments which required to install large amount of wiring lines and can detect dangerous gases as well [2].

1.1. Underground coal mines
At present, mining is a task that annually takes many lives because the vast majority of companies that do this work do not have detection methods to provide safety for workers inside an underground coal mine. Extreme security actions would avoid fatal accidents that every year leave great human losses, material, social damage and a host of problems due to diggings and emissions of toxic gases. In most cases, 95% of underground coal mines in Colombia do not have a system for detecting toxic gases in real time, as evidenced by experimental work [3].
1.2. Gas monitoring
Inside the underground coal mines is necessary to implement a permanent and continuous monitoring of methane (CH4) and oxygen gases in transport and ventilation [4]. Also, where have active fire outbreaks must be implemented a system of permanent and continuous monitoring of carbon monoxide (CO) and oxygen (O2). These gases should be monitors continuously and permanently in places where vehicles are used with internal combustion engine. Before each use of the measuring equipment, it must make a clear verification of the range (±10% standard value of the pattern). In this study, Xbee wireless modules for communication between nodes were implemented in gas sensor arrays, which are important part to develop an electronic nose in order to detect toxic gases usually generated in coal mines [5].

2. Materials and methods
The following section shows the components used for the design and development of multisensor prototype. This consists basically of a sampling and measurement system than comprises of a set of six metal oxide gas sensors (Type MQ) and a data processing stage used to classify a set of acquired samples by data acquisition card wirelessly. The wireless technology used in this study was ZigBee, which is a communication protocol that can use a single coordinator, one or more routers and as well as several mobile devices (i.e., e-noses).

2.1. Communication model
The topology of the wireless communication system is a tree-like structure, which can be used in confined spaces. For this reason, it is possible to implement the distribution of an electronic nose within a location with limited space, such as a coal mine or indoor environments [6]. In turn, it is possible to obtain better communication between nodes of the same type. The model was implemented with a standard configuration API (Application Programming Interface), which allows more information node and thus know the status of it. The data or frame is transmitted in serial mode to the coordinator, which is interconnected to a Xbee-USB-PC adapter to send requests to the present node and handles this request depending on the case (i.e., routers or several e-noses. If an end-device were selected, this will indicate a default router which will serve as a repeater for that coordinator receives data from the remote point.

2.2. Data processing methods
A total number of 41 measurements were acquired with the multisensor system from a set of toxic gas cylinders for calibration of the system (Table 1). A brief description of these gases and measurements (#M) are given below: Gas mixture (9M): CH4 (2.5 %), H2S (25 ppm), O2 (18%), CO (100 ppm), Carbon monoxide (12M): CO (100 ppm), Liquefied gas (10M): LG (98% purity), Carbon dioxide (9M): CO2 (2.5 %).

All measures in voltage values were acquired and transformed in conductance values. We used the static parameters to extract information from sensor array where the most relevant information from the sensor response was obtained to reduce the amount of information of data set. The main static parameters such as: maximum conductance (Gmax), minimum conductance (Gmin), initial conductance (Gi) and final conductance (Gf) were extracted to calculate the conductance increment (ΔGmax= (Gmax-Gmin)), normalized conductance increment or also called fractional difference maximum (ΔGnormax=ΔGmax/Gmax)), absolute differences logarithm (ΔGlog=log (|Gmax-Gmin|) and absolute fractional differences maximum logarithm (ΔGlog=log (|Gmax-Gmin|/Gmax)). Thus, more combinations could be calculated and applied using Gi and Gf. The data matrix size was 41x6 that corresponded to 41 measurements and 6 variables, which was used in order to determine the success rate of data classification from the sensor responses.

Linear multivariate methods are often used for discrimination, reduction, identification and classification of different Volatile Organic Compounds (VOC’s). In this study two linear transformation PARC methods and a Neural Network were applied to classify a set of toxic gases.
The data set were pre-processed using a statistical parameter such as *increased maximum*, see equation (1), to obtain the discrimination of the data. Finally, the normalized data were processed applying pattern recognition methods such as Principal Components Analysis (PCA) and Discriminant Function Analysis (DFA).

\[
\Delta_{\text{max}} = G_{\text{max}} - G_{\text{min}}
\]

(1)

where, \( G_{\text{max}} \) is the response or the maximum conductance (resistance inverse) of the sensors in presence of odour, and \( G_{\text{min}} \) is the steady-state of minimum conductance or baseline signal.

Once trained the system, a new measure was acquired randomly through the cylinders in order to discriminate which class belongs.

**Table 1. Identification of categories**

| # Gas containers | Compound                        | PCA Labels | DFA Labels | Categories Colour |
|------------------|---------------------------------|------------|------------|-------------------|
| 1                | Gas mixture CH4 (2.5 %), H2S (25 ppm), O2 (18%), CO (100 ppm) | A          | Δ          | Yellow            |
| 2                | Methane CH4 (2.5 %)             | B          | ◊          | Red               |
| 3                | Carbon monoxide CO (100 ppm)    | C          | □          | Green             |
| 4                | LG(Liquefied gas) butane (98% purity) | D          | *          | Blue              |
| 5                | Carbon dioxide (2.5 %)          | E          | ●          | Purple            |

**3. Results and discussion**

Figure 1 illustrates the electronic nose prototype which was developed in order to be applied in indoor environments but with alternative to cover a wide range of applications, in this work we developed an Electronic Nose to detect toxic gases frequently generated in underground coal mines. Although the multisensory system has not been used to tests on-site (inside of mine), the wireless communications between coordinator and routers was successful, reaching a distance of 110 meters indoors (obstacles in classrooms).
The data pre-processing and processing algorithms were done with tools provided by Matlab having added a Graphical User Interface (GUI). It is important to clarify that both PCA and DFA were used by being linear supervised and unsupervised methods to project data set from different sensors to a two-dimensional plane [7]. Figure 2 depicts the classification realized with the PCA and DFA methods for discrimination of the data set. PCA was selected in this application because is an effective unsupervised linear method to project data from several sensors to a two-dimensional plane and it is possible to discriminate easily the data set as well. Figure 2(a) illustrate the clusters of gas mixture (A, yellow colour) and CH$_4$ (B, red colour) compounds which are very close, so this could have some overlaps with samples near these two groups.

Figure shows the first two principal components represented in 99.74% of the variance in the data set. DFA technique was applied to discriminate the groups or clusters, to define the better way to separate groups and remove variables which are little related to group distinctions. Therefore a number of two latent variable (factors) of a linear combination of independent variables were chosen. Figure 2(b) shows the results of DFA that were obtained from 41 measurements mentioned above, where a new measure carried out with 2.5% of CH$_4$ was classified correctly with the cluster of gas mixture (i.e., included 2.5 % of CH$_4$). It was observed that the distance among the different groups showed good discrimination in both cases, achieving an adequate selectivity and repeatability of the system and demonstrating a high performance of the equipment. In addition, this analysis showed that DFA is a good supervised method to distinguish different varieties of toxic gases present in underground coal mines. The two first factors achieved up 99% of variance in the data set.

![Figure 2](image-url)

**Figure 2.** a) PCA graph with different types of cluster (Toxic gases) and new measurement projection, b) DFA performed on the mean-centred response matrix with statistical parameter Δmax

In this study a supervised method such as probabilistic neural network was applied to classify the data set, it provides a solution to measures classification problems. PNN was performed by Specht [8]. Figure 3 illustrates the PNN response using normalized data and targets, in order to estimate the classification where a success rate was obtained with 41 measures and an average of 97.6 %. Clearly the new measure of methane gas was grouped within the gas mixture category, for obvious reasons the general classification was 100%. The cross validation method generates N evaluation procedures (1 for each measurement), for each iteration a different measurement was left out, while the remaining measurements were used for network training (the one not used for training). This is repeated N time (one for each measurement) so that the final result is the average success of entire iterative process. This method did not present over-fitting because the evaluation measurement was not used in training data.
4. Conclusions
The sensitivity and selectivity obtained by the WEN system was good and the repeatability shown by the equipment was satisfactory. The e-nose developed on a ZigBee wireless network shows the viability to implement a measurement instrument to detect VOCs in indoor environments (Underground Coal Mines) due to low-power consumption, reliability and high portability. Through the results obtained with the WEN is possible to develop real-time applications for monitoring and control of various processes, requiring a multisensory system of such characteristics to be implemented in different sectors (e.g., industrial sector, environmental, health, etc). The pattern recognition methods (DFA and PCA) were applied on the normalized array and two first discriminant factors or scores reached more than 99% of variance. The classification of data set was successful achieving 100% with the PNN supervised learning.

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