Wireless Sensor Network for Air Quality Monitoring and Control

Patricia Arroyo, Jesús Lozano*, José Ignacio Suárez, José Luis Herrero and Pablo Carmona

Industrial Engineering School, University of Extremadura. Av. Elvas s/n, Badajoz (SPAIN)
jesuslozano@unex.es

A network of low-power wireless sensors for the detection of air quality pollutants (acetone, toluene, ammonia , formaldehyde, ethanol, benzene, dichloromethane, acetic acid, xylene and dimethylacetamide) is described in this paper. The network consists of several sensor nodes responsible for receiving information and wirelessly, through ZigBee protocol, sending it to a gateway connected to the Internet. A cloud infrastructure is used to store the data of each node and to perform the data processing. Several autonomous nodes equipped with four different gas sensors are used to measure the pollutants concentration in air. Each node also includes a pump and a 3-way electric valve to carry the air samples to the sensor cell. The 3-way electric valve can be operated in order to switch between reference clean air or gas samples from the vials containing the samples. The communication between nodes and the gateway is based on the standard IEEE 802.15.4 (Zig-Bee protocol). Data processing and analysis have been performed with the use of principal component analysis (PCA) and artificial neural networks.

1. Introduction

The environmental pollution is a major problem both in developed and emerging countries. That pollution has harmful effects on the health of living beings, and therefore, the International Agency for Research on Cancer (IARC) has classified air pollution as carcinogenic to humans (Loomis et al., 2013). Consequently, there is a growing global concern in this regard, and governments around the world are establishing demanding environmental quality standards. Against this background, to get a reliable, compact and inexpensive system for the detection and control of pollutants that give rise to environmental problems, is still a goal to achieve.

This paper mainly focuses on making measures with some systems designed for the detection of target gases at different concentrations and environmental conditions. In addition, it is also based on the characterization of the response of the sensor and on techniques grounded on artificial intelligence to process the sensor data in order to optimize the detection of compounds and contaminants. Therefore, wireless sensor networks (based on sensor nodes motes and smart devices) are implemented to perform field measurements.

1.1 WSN

Wireless sensor networks (Yick et al., 2008) (WSN) have gained worldwide attention in recent years. The development of intelligent sensors has been facilitated by the rise of Micro-Electro-Mechanical (MEMS) technology systems. These sensors are small, with limited processing and computing resources, and inexpensive compared to traditional sensors. They can perceive, measure, and collect information from the environment and, based on some local decision-making processes, they can transmit data to the user.

The smart sensor nodes are low-power devices equipped with one or more sensors, a digital processor, some memory, a power supply, a radio, and an actuator. A variety of mechanical, thermal, biological, chemical, optical and magnetic sensors can be connected to the sensor node to measure environment properties. Because the sensors have limited memory and nodes are typically developed to place them in difficult accessed locations, a radio is implemented to establish wireless communication and to transfer the data to a base station. Several studies related to the use of gas sensors in wireless sensor networks have been

developed, i.e. a WSN to detect gas leaks (Brunelli and Rossi, 2014), or a device to monitor and prevent possible explosions of gas and coal (Deng and Chen, 2010).

However, WSNs have limitations in terms of memory, energy, computing, communication and scalability. In parallel, cloud computing is becoming a promising technology to provide a massive pile of computing, storage and software services.

1.2 Sensor Cloud

Wireless sensor networks allow to develop many applications that acquire and process information from the physical world. Similarly, the possibility of sharing distributed resources is carried out through the use of data clouds. Cloud computing is a term used to describe both a platform and an application type. A platform cloud computing server can be configured or reconfigured as needed, which is an alternative to having local servers. On the other hand, a cloud can describe an application accessible via the Internet. Cloud computing servers from the Internet are responsible for responding requests at any time. In this approach, services can be accessed through an Internet connection from any mobile or fixed device located anywhere. The use of cloud data in order to share information from sensors on WSNs is a promising technology called "Sensor Cloud" (Wang et al., 2016).

2. Material and Methods

A WSN for measuring gases has been developed in this project. This proposal consists of several sensors nodes that send and receive information (following the ZigBee protocol) through a gateway. With the use of an Ethernet connection, the gateway forwards sensor data to a cloud where they are stored in .xml format for subsequent processing (Figure 1).
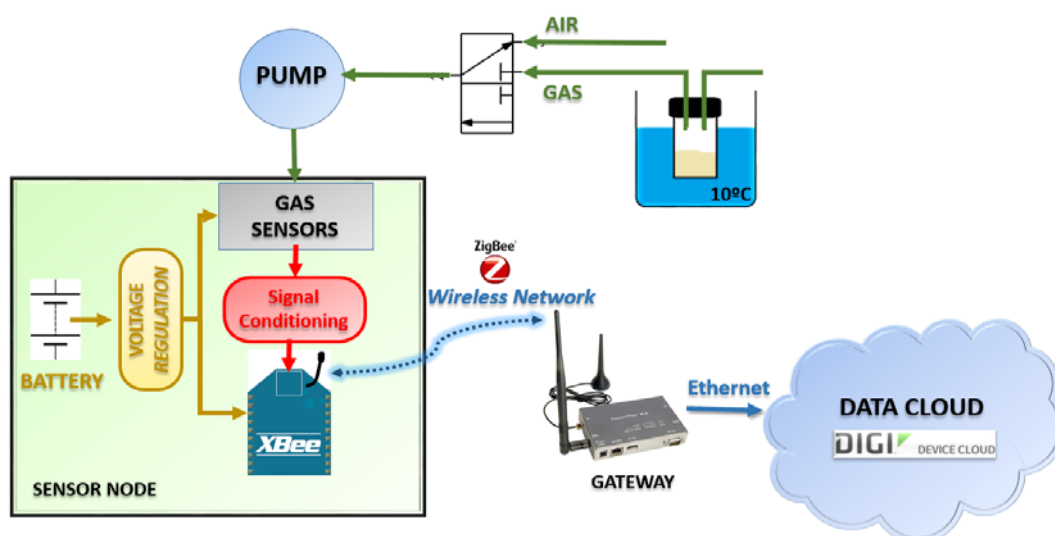

Figure 1: System block diagram.

2.1 Nodes

Sensor nodes are low cost, small size and low power consumption systems. They are able to collect information about the existence of gases in air using different types of gas sensors. The designed node is shown in Figure 2 and consists of the following devices:

- XBee and XBee PRO modules: these modules communicate with the built-in gateway coordinator node. They are RF modules manufactured by Maxtream, working within the 2.4 GHz band, with ranges of 100m (Xbee) and 1500m (XBee PRO).
- Power supply: it is mainly composed of a 3.7 V lithium battery and some DC-DC converters.
- Gas sensors: there are 4 resistive MEMS sensors. Specifically, they are the TGS 2600 and TGS 2620 models.
- Signal conditioning circuits: they are responsible for adapting the signals to the required range for the correct operation of the communication modules.

Nodes also include a pump and a three-way electric valve for driving air samples or the reference gas to the sensor cell.
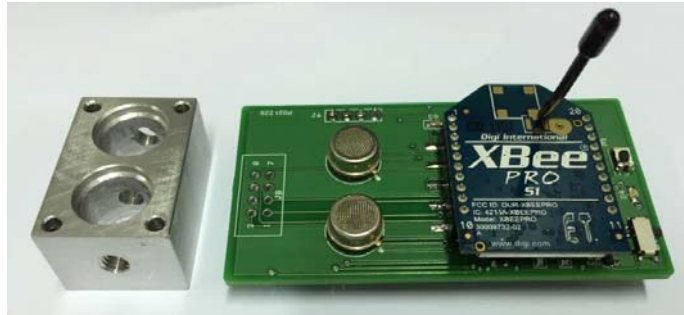
Figure 2: Sensor node developed.

2.2 Wireless Net
The wireless net fulfills the specification for a suite of high-level ZigBee communication protocols. In turn, ZigBee is based on the IEEE 802.15.4 standard (Baronti et al., 2007). It is intended for being used in secure communications applications with low data rate and long-life battery. It differs from other existing technologies because of its low power consumption, its mesh network topology and its integration capacity.

In the network created in this work, a 16-bit addressing mode is used due to the low number of nodes in the network.

2.3 Internet gateway and data cloud storage
The information collected by the sensor nodes is sent to the gateway: ConnectPort X4 (Digi). This gateway offers a variety of LAN/WAN interface options for end-to-end networking of remote devices including XBee-enabled devices. Moreover, a friendly Python development environment enables custom applications to run locally.

In this study, a Python application has been developed to separate and pre-process the information received from several nodes and then to send and store data in a cloud. Specifically, an .xml file is stored by each node in Device Cloud. To this end, the software provided by the manufacturer, "DigiESP for Python" has been used. Digi Device Cloud is a machine-to-machine (M2M) platform-as-a-service that enables remote access and control of the Digi cellular routers and gateways (Figure 3). Devices are associated with the server through the Internet or other wide area network connections. That, allows the communication between the devices, the server, and the user applications. An important part of this communication is the data transfer from a device to the server. Users can control devices by sending commands or scheduling tasks. Devices can upload data to Data Streams on Device Cloud which are then available for pushing notifications, alarms, or retrievals by Web Services clients.

Figure 3: Device Cloud screenshot. The Device Management tab shows devices connected to the cloud and their parameters.

2.4 Gas extraction system
Within all odor extraction techniques available (Lozano et al., 2007), the headspace technique modified for extraction of gases from glass vials has been used. Headspace technique consists of isolating the gas sample

in liquid state in a hermetically sealed container, in our case a vial. Thereby, volatile components released by the liquid are maintained in the upper region of the container thereby forming a gaseous sample in equilibrium with the liquid. Afterwards, the detached volatile components are transported from the sample to the sensors.

2.5 Data Processing

The processing step is carried out once the sensor signals have been acquired and stored in text files. Specifically, the saved data are the time, sensor responses and other parameters such as ambient temperature, electrovalve status, etc.

As shown in Figure 4, this process can be divided into four stages: feature extraction and signal pre-processing, dimensionality reduction, classification, and decision making (Gutiérrez-Osuna, 2002). The first block in the figure represents the set of sensors and the instrumentation, whose output is the file with the temporary measurements carried out. The programs have been implemented using Matlab and Signal Processing and Neural Networks toolboxes.

During the first phase, the pre-processing of the measured data from the sensors is performed through a program developed in Matlab. The input of that program is the text file of measurements previously stored. The characteristic value is then extracted and a single representative value of each measured sample is obtained. This value is calculated using the relative resistance algorithm. It is the division of steady-state value and the value of the reference gas.

The second phase aims to reduce the dimensionality of the extracted data. With this aim, the technique of principal component analysis (PCA) is used. The PCA technique is a statistical summary of the information, or reduction of data size (number of variables). The new principal components or factors will be a linear combination of the original variables and independent among each other. The main components are chosen such that there is maximum variance of data in the smallest possible number of them, being orthogonal to each other (no correlation among them). The PCA method eliminates any redundancy or correlation existing in sensor responses. Typically the n-dimensionality of the problem is reduced to the first two eigenvectors (first two principal components) that contain most of the information (Marco et al., 2012).

In the next step, the resulting low dimension vector is used for prediction. The tasks to be developed are clustering, regression or classification. In the clustering method, the aim is to learn the structural relationships between different pollutants. In regression tasks, the objective is to predict a set of properties (e.g. strength, quality, etc.) of an analyte. Finally, classification tasks are used in order to identify an unknown sample as a class within a set of learned contaminants.

The final stage of the Pattern Recognition system designed in this paper is to classify each pattern automatically. This is possible through a technique based on the use of neural networks. These types of algorithms (based on the biological nervous system) are sets of elements of simple calculation, usually adaptive, massively parallel and interconnected with a hierarchical organization.

It should be pointed out that, finally, an error estimation of the trained model is obtained by using validation techniques.
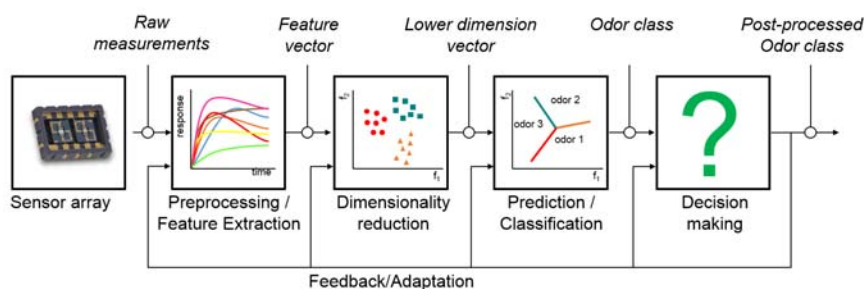

Figure 4: Data processing block diagram.

3. Results

3.1 Measurement setup

The prototype uses headspace as the sampling system: the headspace of samples stored in 15 ml vials is carried to the sensor cell by using an integrated pump. The measurement setup includes cycles of 60 s of adsorption and 540 s of desorption. Gas sensors were operating at different temperatures between 400 and 500ºC. At least 20 measurements were taken from the samples prepared as solutions of several compounds in water: blank water (W), acetone (Ac), toluene (To), ammonia (Am), formaldehyde (Fo), ethanol (Et), benzene (Be), dichloromethane (Dc), acetic acid (AA), xylene (Xy) and dimethylacetamide (Da). The average

response of each sensor to the measured samples is shown in Figure 5. It can be observed that a different profile is obtained for each sample.
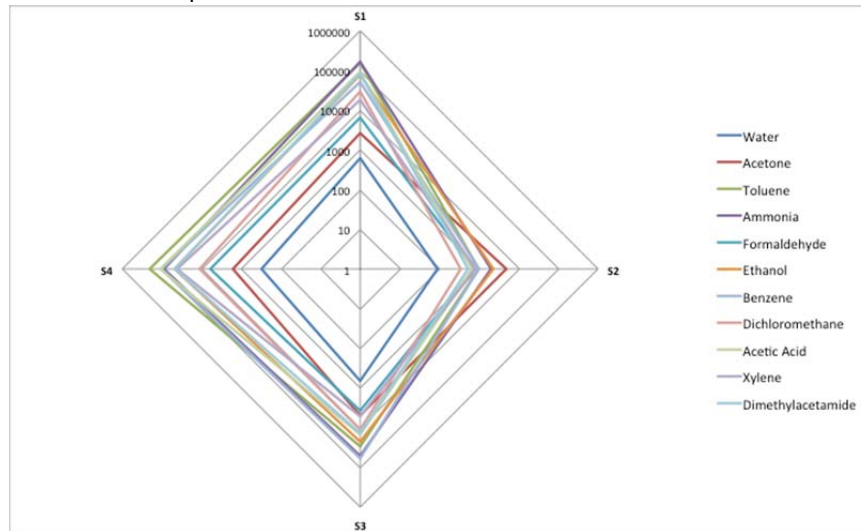

Figure 5. Radial plot of sensors response to the measured samples.

3.2 Results

Once the measurements of the samples were performed, the data were preprocessed, and after feature extraction (relative response baseline manipulation and sensor normalization), PCA was performed on the data to reduce their dimension in order to show it in a plot. Figure 6 shows the plot for the two first principal components of samples of gases or odours (generated from headspace of adulterated water with 10 compounds). It can be noticed that the clusters of the different pollutants are clearly separated although some partial overlapping among them appears.
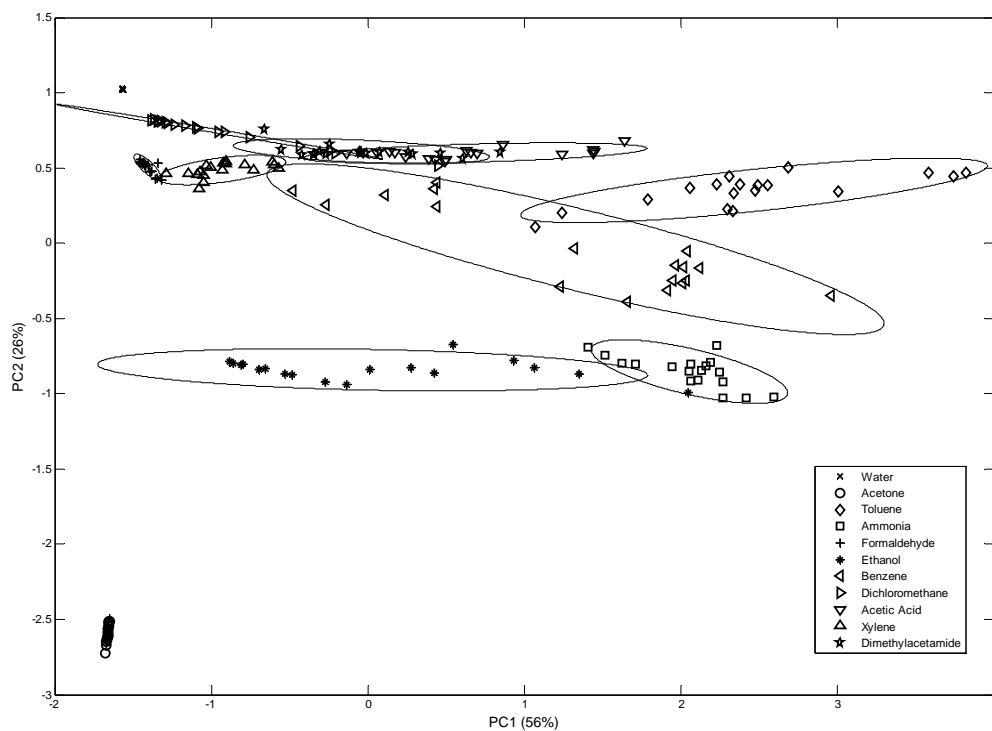

Figure 6. PCA Score Plot of measurements performed with one of the sensor network nodes.

These results are confirmed applying several types of Artificial Neural Networks (ANNs) classifications. ANNs classifiers are used because it offers a prediction response similar to human sense of smell. The response depends on the descriptors used in learning. Two common ANNs have been used: Probabilistic Neural Network with Radial Basis Functions (RBF) and Feed Forward Neural Network with Backpropagation (BP) learning algorithm. Leave One Out crossvalidation is used to obtain a performance estimation. The obtained success rate (percentage of cases correctly classified when validating) was 93,9% with the RBF network and 95,4% with the BP network. The confusion matrix (predicted vs. real value) obtained in Leave One Out validation with both networks is shown in Table 1. The results confirm that the proposed sensor network developed has been able to discriminate with a success rate near to 100% among the different samples.

Table 1. Confusion matrix obtained in LOO validation of Radial Basis PNN | BP networks respectively.

	W		Ac		To		Am		Fo		Et		Be		Dc		AA		Xy		Di	
W	18	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ac	0	0	18	18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
To	0	1	0	0	18	15	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1
Am	0	0	0	0	0	0	17	17	0	0	1	1	0	0	0	0	0	0	0	0	0	0
Fo	0	0	0	0	0	0	0	0	18	18	0	0	0	0	0	0	0	0	0	0	0	0
Et	0	0	0	0	0	0	2	1	0	0	16	17	0	0	0	0	0	0	0	0	0	0
Be	0	0	0	0	0	0	1	0	0	0	0	0	14	15	1	2	0	1	0	0	2	0
Dc	0	0	0	0	0	0	0	0	0	0	0	0	1	0	17	17	0	0	0	0	0	1
AA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	17	18	0	0	1	0
Xy	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	17	18	0	0
Di	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	16	18

4. Conclusions

A home-made and home-developed gas sensor network based on Zigbee wireless communication is used for discrimination of pollution in water samples. Principal Component Analysis and classification with Artificial Neural Networks show good results (more than 95%) in discrimination of samples.

Reference

Baronti P., Pillai P., Chook V.W.C., Chessa S., Gotta A., Hu Y.F, 2007. Wireless sensor networks: A survey on the state of the art and the 802.15.4 and ZigBee standards. Computers Comunications, 30, 1655– 695.

Brunelli D., Rossi M., 2014. Enhancing lifetime of WSN for natural gas leakages detection. Microelectronics Journal, Vol. 45, Issue 12, 1665–1670

Deng M., Chen Q., 2010. Coal and gas outburst monitoring system based on WSN. Procedia Engineering, Vol. 7, 387–391

Gutierrez-Osuna R., 2002. Pattern Analysis for Machine Olfaction: A Review. IEEE Sensors Journal, Vol. 2, no. 3, 189-202.

Loomis D., Grosse Y., Lauby-Secretan B., El Ghissassi F., Bouvard V., Benbrahim-Tallaa L., Guha N., Baan R., Mattock H., Straif K., 2013. The carcinogenicity of outdoor air pollution. Lancet Oncol, 14(13):1262-3.

Lozano J., Santos J.P., Gutiérrez J., Horrillo M.C, 2007.Comparative study of sampling systems combined with gas sensors for wine discrimination. Sensors and Actuators B: Chemical, 126, 616-623.

Marco S., Gutiérrez-Gálvez A., 2012. Signal and Data Processing for Machine Olfaction and Chemical Sensing: A Review. IEEE Sensors Journal, Vol. 12, 11, 3189-3214.

Wang, S-L., Chen Y.L., Kuo A. M-H., Chen H-M., Shiu Y.S., 2015. Design and evaluation of a cloud-based Mobile Health Information Recommendation system on wireless sensor networks. Computers & Electrical Engineering, 49, 221-235, DOI:10.1016/j.compeleceng.2015.07.017

Yick, J., Mukherjee B., Ghosal D., 2008. Wireless sensor network survey. Computer Networks Volume 52, Issue 12, 2292–2330.