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Bluetooth Electronic Nose for Odour Monitoring and Control

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A novel miniaturized and battery operated electronic nose (60x60 mm) for measuring different odorous compounds is presented in this paper. It can be connected with any smart device or personal computer through a Bluetooth link, which is used for commands and measurement data exchange based on a simple protocol. The system is controlled by a high performance 8-bit microcontroller and includes four miniaturized metal oxide (MOX) sensors for odour detection, an integrated sensor for temperature and humidity measurement, and the appropriate signal conditioning circuits.

1. Introduction

Artificial senses like hearing, sight and touch have already been implemented in smartphones and other smart devices. The sense of smell is often considered as a minor sense, but it is only minor in the sense that they are less studied and have less of the brain devoted to them than vision and audition. Just as sound is the perception of changes in air pressure and sight is the perception of light and colors, smell is the perception of chemicals in the air.

Nowadays, society is being witness of the birth of Internet of Things (IoT). As the online Oxford Dictionary suggests, IoT is “The interconnection via the Internet of computing devices embedded in everyday objects, enabling them to send and receive data” (Oxford University Press, 2018). Those devices are becoming more and more part of citizens daily lives thanks, to some extent, to the smartphones upsurge. The massive use, connectivity and processing power of smartphones makes them ideal candidates to implement distributed and ubiquitous measurement systems, especially in the detection of contaminants and monitoring of air quality in the citizens surroundings. This way, some protocols could be implemented in order to protect their health and improve their wellness. The development of micro electro mechanical systems (MEMS) based environmental sensors with low size and power consumption makes them appropriate for being implemented in IoT portable devices connected to smartphones, tablets or even wearable devices.

On the other hand, Bluetooth technology has become an integral part of our lives. From wireless headphones to smartbands, we use Bluetooth everywhere and the number of devices and gadgets that could be connected with them are growing more and more. Following this approach, many electronic noses (e-noses) that has been built for odour recognition uses that kind of link. As an example, a description of a portable, but not compact, gas sensor systems for detecting and quantifying traffic pollution appears in (Elen et al., 2012). Measurement data are stored into a SD card and later transmitted to, through a Bluetooth connection, a PC or a smartphone. Bluetooth communications between a personal digital assistant (PDA) and a compact e-nose, with one in-house manufactured MEMS gas sensor, is also used in (Moon et al., 2013). Bluetooth is the natural replacement to the classical RS232 wired connection as shown in (Tiwari et al., 2014), where a dongle is used to communicate the digital multimeter of an e-nose with a smartphone.

The miniaturized e-nose presented in this work, which makes use of a Bluetooth link for transmitting data on-the-fly with a smartphone, incorporates several MEMS sensors for air quality monitoring and an integrated temperature and humidity sensor, which usually is not included in many e-noses (Figure 1). Almost any modern smartphone includes a GPS system, which can be employed as an additional e-nose sensor (Zhang et al., 2017).

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Figure 1: Prototype of the electronic nose

In any e-nose, data processing is a key part for odour recognition and classification, where different existing techniques are used. In particular, the relative resistance (RR) technique (Gardner, 1991) is used in the feature extraction phase of the sensor signals. To achieve a reduction of the dimension of the data, the principal component analysis (PCA) technique is used (Esbensen and Geladi, 2009), which is based on the expansion of Karhunen-Loeve (Kittler and Young, 1973). To implement algorithms for classification tasks, networks with Radial Basis Functions or probabilistic neural networks (PNN) have been used (Specht, 1990). Finally, leave-one-out cross-validation (LOOCV) have been used to determine the validity of the classification models with neural networks (Arlot and Celisse, 2010).
In this paper, a small prototype of an electronic nose with Bluetooth connection is presented here. Some laboratory experiments have been carried out for studying the ability of the device to discriminate some polluting compounds, such as benzene, carbon monoxide (CO), and nitrogen dioxide (NO_2), at different concentrations.

2. Electronic Nose

2.1 Block diagram

The e-nose integrates four analogue MOS gas sensors in three small chips from SGX Sensortech: one in MiCS-5914, one in MiCS-5526 and two elements (RED and OX) in MiCS-4514. Temperature and humidity sensors come in a small integrated circuit (SHT21) from Sensirion, where information is obtained through an I^2C bus. Up to 12-bit and 14-bit resolution can be obtained in humidity and temperature readings, respectively.
The block diagram of the system is depicted in Figure 2. The center piece is a PIC18F46K80 high performance 8-bit microcontroller from Microchip. It includes up to 11 analog to digital (A/D) 12-bit input channels, however only four are used for measuring the gas sensors resistances. Analogue signal conditioning circuits and low pass passive filters are included in the signal paths. The heating elements of those sensors are governed with bipolar transistors through a PWM signal each, which are generated with the four Capture/Compare/PWM (CCP) modules of the microcontroller. The Master Synchronous Serial Port (MSSP) is used for establishing an I^2C communication, with the microcontroller acting as a master and the SHT21 device as a slave. One of the two Universal Synchronous Asynchronous Receiver Transmitter (USART) modules that incorporate the microcontroller has been used for establishing a serial communication with a smartphone through an RN42XV Bluetooth module from Microchip. The operating speed of the microcontroller can reach 64 MHz, however, due to power consumption concerns it has been reduced to 32 Mhz, which is a good compromise between processing speed and consumption.

The system is powered from a 3.7 V Li-polymer rechargeable battery, from which two different voltages are obtained: +3.3 V for the Bluetooth module and the SHT21 device, and +5 V for the rest. Voltages are generated with a high efficient DC/DC step-down converter for +3.3 V (based on LM3671) and a step-up one for +5 V (based on MCP1642). A battery charger with a MCP73831 integrated circuit is also included.

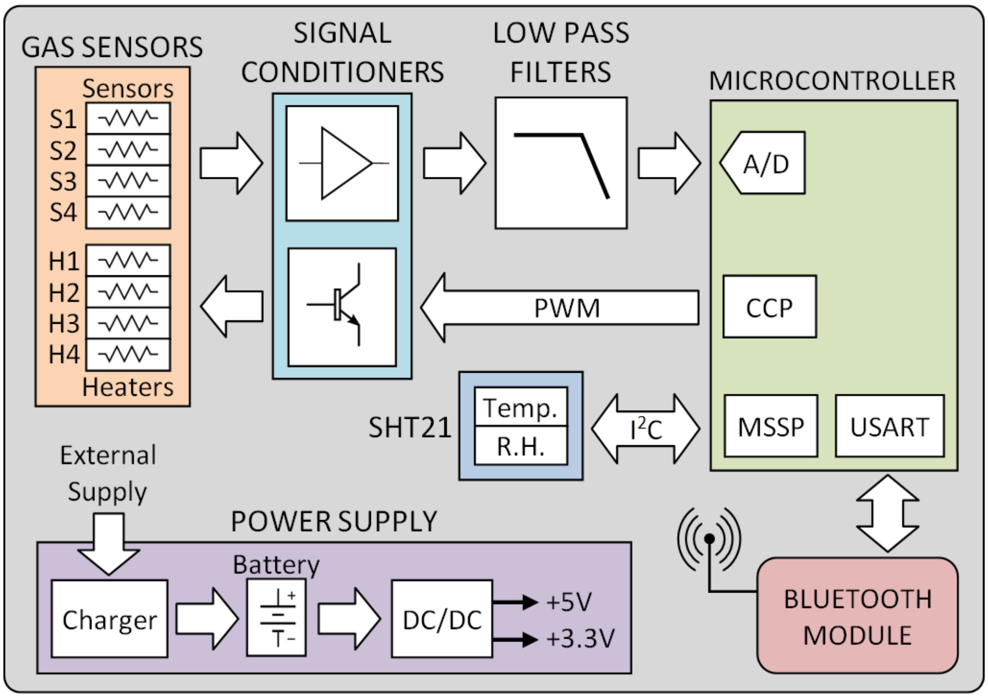

Figure 2: Block diagram of the prototype of electronic nose

2.2 Communication protocol

A simple ASCII-based protocol has been established for the wireless communication between the microcontroller and a high performance device (smartphone, PC, ...), where intensive data processing is carried out. Control commands can query data from an individual sensor or from the whole group. There are some commands for starting and stopping the experiment, and for setting heaters values. In the latter case, single or continuous data frame can be issued. A data frame is generated and transmitted every sample time. Data fields are separated by horizontal tabs and frames are finished with carry return and line feed characters. Firstly, heater values are transmitted, followed by ambient temperature and humidity, and then gas sensor raw data. A typical frame, with explanation of its different fields, is depicted in Table 1.

Table 1: A typical frame and interpretation of data fields

Frame: H1 \t H2 \t H3 \t H4 \t TP \t RH \t S1 \t S2 \t S3 \t S4 \r \n

Field	Description	Range
H1 ... H4	Heater values (PWM duty cycle)	0 % – 100 %
S1 ... S4	Gas sensor 12-bit reading values	0 – 4095
TP	Temperature	-45 to + 125 ºC
RH	Relative Humidity	0 % – 100 %
\t	Data separator (horizontal tab)	-
\r\n	End of frame (carry return + line feed)	-

3. Measurements setup

A homemade automatic gas generation system has been used for testing the prototype. That system allows up to four compounds mixing from gas cylinders with desired flow rates and concentrations. It consists of four inputs controlled by four flowmeters and four electrovalves, a gas expansion module, and some security measures to complete the process. In addition, it allows to program customized timed measurement cycles,

thus achieving more accurate measurement process. The control system is based on a PLC with a SCADA system included. Management is done via a touch screen on the front.
In this case, different concentrations of benzene, CO, and NO_2 have been generated. The scheme of the measurement system is shown in Figure 3, where the target pollutant coming from gas cylinders is diluted in dry air in the desired ratio. The outflow, set at a flow rate of 100 ml / min, is passed through the gas sensors of the measuring device. Each measurement cycle consists of a 60-second adsorption phase (dissolved pollutant) and a 540-second desorption phase (dry air).

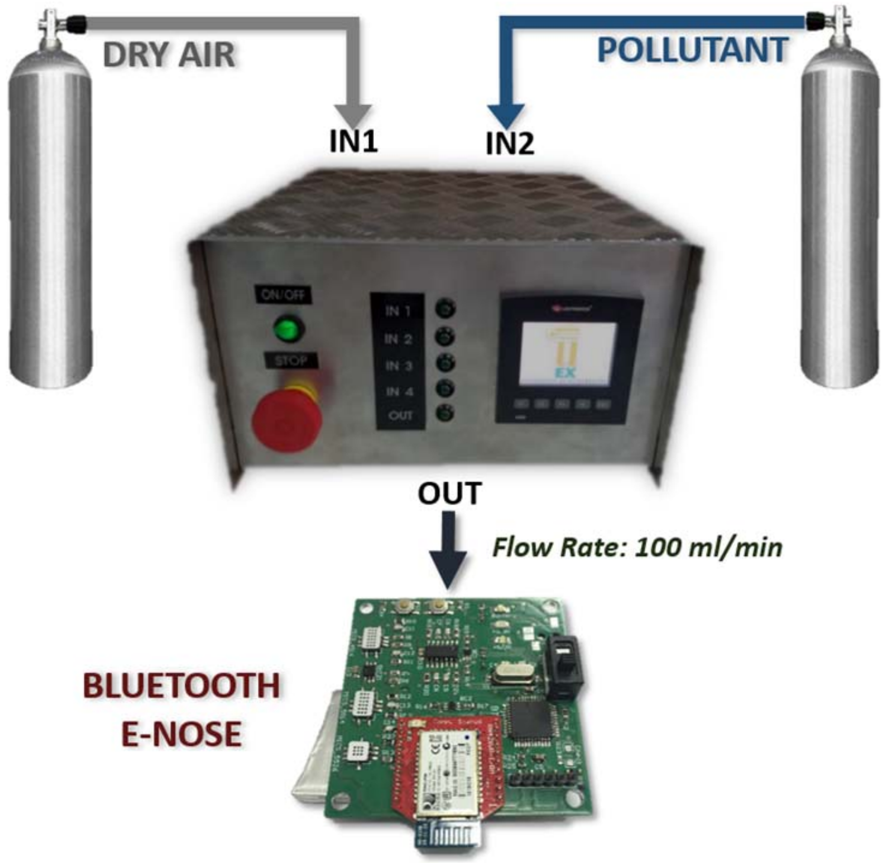

Figure 3: Diagram of the measurement setup

They were generated concentrations of 5%, 10%, 15% and 20% in dry air of the dilution contained in the available cylinders (Benzene: 3.01 ppm; NO_2: 1.6 ppm; CO: 48.6 ppm). For each pollutant, 20 measurements were made at each concentration. In all cases, the first measure was removed, since the systems were not yet stabilized and the conditions were not the same. Therefore, 19 measurements of each compound have been finally used for processing.

4. Results

Once all the samples have been taken, the data processing is carried out. This process can be divided into four stages: feature extraction and signal preprocessing, dimensionality reduction, classification and decision making.
First, the feature extraction from each of the measurements was performed. To this end, we used the method of relative resistance, where each value corresponds to the ratio of the stable reference gas value and the minimum value obtained in the sample measurement. For dimensionality reduction, it is performed the principal component analysis (PCA). It is a technique that allows to reduce the data set, losing as little information as possible. The new main components are a linear combination of the original variables, and also independent of each other. The first two main components are represented in a graph for analysis (Figure 4). The different pollutant compounds are represented in the same color. It can be noted that as the concentrations are decreasing, areas of different compounds are approaching each other. For areas of lower

concentration of CO and NO_2, overlap comes to appear. In addition, some areas of close concentrations also overlap for benzene and CO. However, in general, separation between the different areas is appreciated.

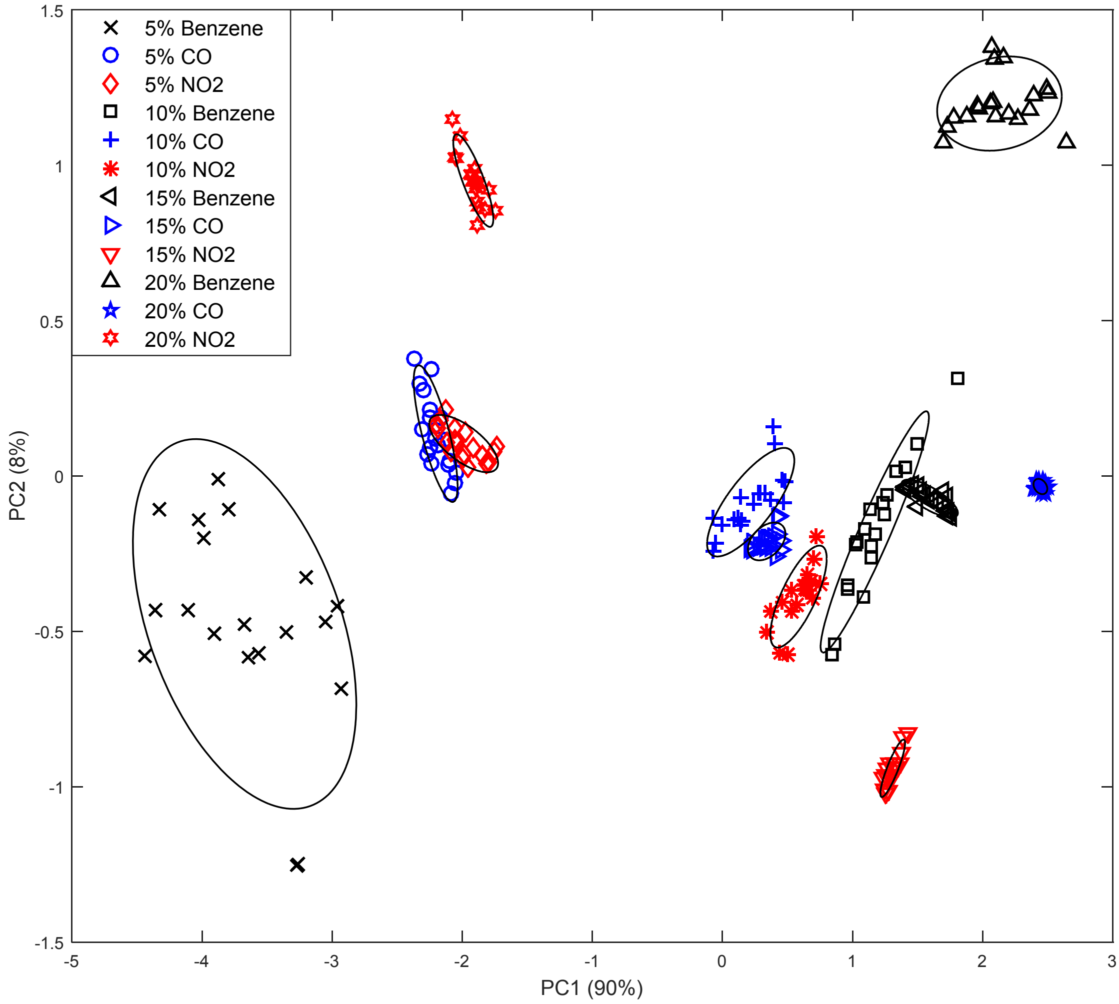

Figure 4: PCA score plot for each pollutant and concentration. Black: benzene; Blue: CO; Red: NO_2

Table 2. Confusion matrix obtained in LOOCV of the PNN

	Be (5%)	CO (5%)	NO_2 (5%)	Be (10%)	CO (10%)	NO_2 (10%)	Be (15%)	CO (15%)	NO_2 (15%)	Be (20%)	CO (10%)	NO_2 (20%)
Be (5%)	19	0	0	0	0	0	0	0	0	0	0	0
CO (5%)	0	18	1	0	0	0	0	0	0	0	0	0
NO_2 (5%)	0	2	17	0	0	0	0	0	0	0	0	0
Be (10%)	0	0	0	18	0	0	1	0	0	0	0	0
CO (10%)	0	0	0	0	19	0	0	0	0	0	0	0
NO_2 (10%)	0	0	0	0	0	19	0	0	0	0	0	0
Be (15%)	0	0	0	1	0	0	18	0	0	0	0	0
CO (15%)	0	0	0	0	0	0	0	19	0	0	0	0
NO_2 (15%)	0	0	0	0	0	0	0	0	19	0	0	0
Be (20%)	0	0	0	0	0	0	0	0	0	19	0	0
CO (20%)	0	0	0	0	0	0	0	0	0	0	19	0
NO_2 (20%)	0	0	0	0	0	0	0	0	0	0	0	19

The classification step aims to make prediction using the low dimensional vector resulting from the dimensionality reduction. In this case, the aim is to study the actual capacity of discrimination of all three pollutants in different concentrations. For this purpose, a PNN was trained.

Finally, the last step in pattern recognition allows error estimation of the trained model by means of validation techniques. In this work, to get more performance to the obtained measurements, leave-one-out cross-validation (LOOCV) was used. It involves generating as many networks as measures are accessible. The confusion matrix obtained is presented in Table 2, where each column represents instances of a predicted class, while each row represents instances of a real class (real values). This matrix allows to visualize the performance of the proposed algorithms. The success rate (percentage of correctly classified cases in the validation versus the total number of cases) obtained was 97.81%.

5. Conclusions

A novel miniaturized prototype of an electronic nose, which includes commercial MEMS gas sensors for odour recognition, has been presented. It also includes a temperature and humidity sensor, which is often omitted in the design of many electronic noses. The use of a Bluetooth module enables the e-nose communications with a smartphone, where data are transmitted on-the-fly and stored for later processing. The ability of the device to discriminate some pollutant compounds (benzene, CO, and NO_2) at different concentrations (5, 10, 15 and 20 %) has been studied by carrying out some laboratory experiments. Principal component analysis technique has been used for dimensionality reduction of data sets. A clear separation between areas of different compounds appears, except for CO and NO_2 at low concentration (5 %). A probabilistic neural network was trained to study the actual capacity of discrimination. The results from the application of the leave-one-out cross-validation technique show that the systems has a very high success rate (close to 98 %) in the pollutant discrimination at different gas concentration.

Acknowledgments

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