

IpNose: Electronic nose for remote bad odour monitoring system in landfill sites

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Electronic noses are intelligent instruments that are able to classify and quantify different gas/odours. Here we suggest the integration of a small form factor computer inside the electronic nose. This concept allows us to easily provide remote connectivity, large data storage and complex signal processing. The evolution of this technology will permit distributed sensing with applications to agriculture and environment. Proposed instrument allows incoming connections for remote control of bad odours in landfill sites. Preliminary approach to this application using commercial sensors and mixture model pattern recognition scheme is exposed.

1 Introduction

Sensors for use in electronic noses need partial selectivity, mimicking the responses of olfactory receptors in the biological nose. In the simplest instrumental approach to an electronic nose, we may find sampling, filtering and sensors module, signal transduction and acquisition, data preprocessing, feature extraction and feature classification. In conventional systems the processing module is provided as a personal computer and is separated from the rest of the system. This module is responsible for data preprocessing, feature extraction and classification. Recent trends in portable computing designs imply the use of embedded systems at low cost and size. This kind of systems can be applied not only to desktop instruments but also at-line analyzers, arrays of distributed instruments over a network, or remotely operated instruments via phone calls to a host computer.

The applications of electronic noses in environment and agriculture fields are generally aiming to substitute slow and laborious laboratory analysis by fast and easy in-field electronic nose analysis. There are many examples of these applications like pollen detection[KAL97], evaluation of malodour in farms[BYU97], wastewater treatment control[ROM00] or grain spoilage[MAG00] [JON97]. Most of these applications show the potential use of electronic noses in order to determine the fungal activity assessment. In the case of grain spoilage, for instance, the odour of grains is in many cases the primary criteria of quality classification. However human smelling should be avoided, not only because is a subjective parameter but also some toxins or mould spores may be hazardous to the health. The use of electronic nose technology in this concrete application would control the quality of grain in different silos for different grain. On the other hand, distributed sensing technology provides a centralised framework in the measurement, analysis and control of the different storage silos. Other application fields are air quality maps over cities by measuring not only contaminant gases like CO, but pre-trained odour quality indices correlated to comfort feeling.

In this paper an instrument capable of realize remote and periodic odour analysis in is proposed . This instrument provides an powerful multi-algorithm pattern recognition engine, including mixture model based classifier. This work evaluates the possible

application of ipNose like electronic nose for landfill sites. In some situations compounds produced are very annoying for neighbourhoods and operators are forced to personally visit landfill sites to prevent or check dangerous degrees of decomposition. Exploratory work for bad odour in landfill sites using a test bench of commercial metal oxide sensors will be exposed comparing a lazy algorithm like *k-nn* with ipNose like *Gaussian Mixture Models*. This is a complex problem as environmental conditions are strong in in-field operation. Many atmospheric phenomena like wide temperature oscillations or rain, can affect the behaviour of the sensors and therefore the classifier.

2 IpNose Instrument

University of Barcelona in collaboration with Wright State University has developed an electronic nose featuring remote connectivity (see fig 1) [PER01]. Design copes with two main objectives: provides a powerful signal processing platform for temperature modulated metal oxide sensors and increases electronic nose features by implementing network/remote connectivity to the analyzer.

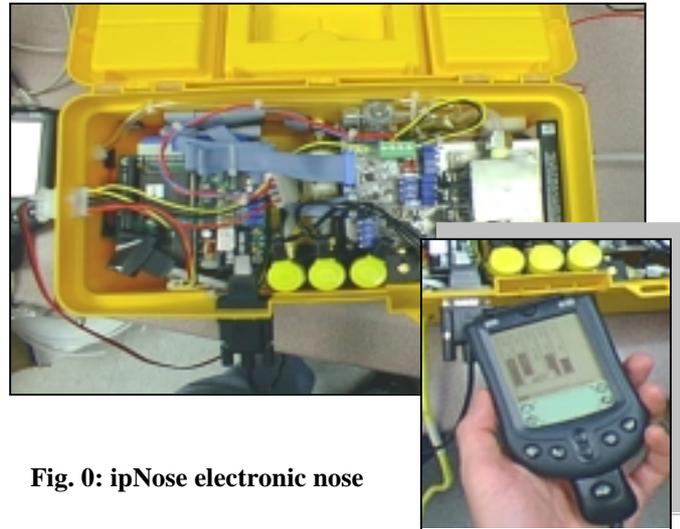


Fig. 0: ipNose electronic nose

Remote Connectivity

Current design of the system provides a versatile platform to be remote controlled or reprogrammed. Once a connection is established commands can be sent to the instrument in order to execute sampling or training, getting current values of sensors, controlling the pump and valves or even reprogram the instrument. These features permit to monitor analysis readings, extracting or modifying internal database contents or even changing signal processing software of a distributed array of electronic noses, all from the same workstation or computer. Although the whole system is remotely operated via TCP/IP under client/server structure, it can send active signals to external systems like emails to the user when samples are getting out of specifications. Another

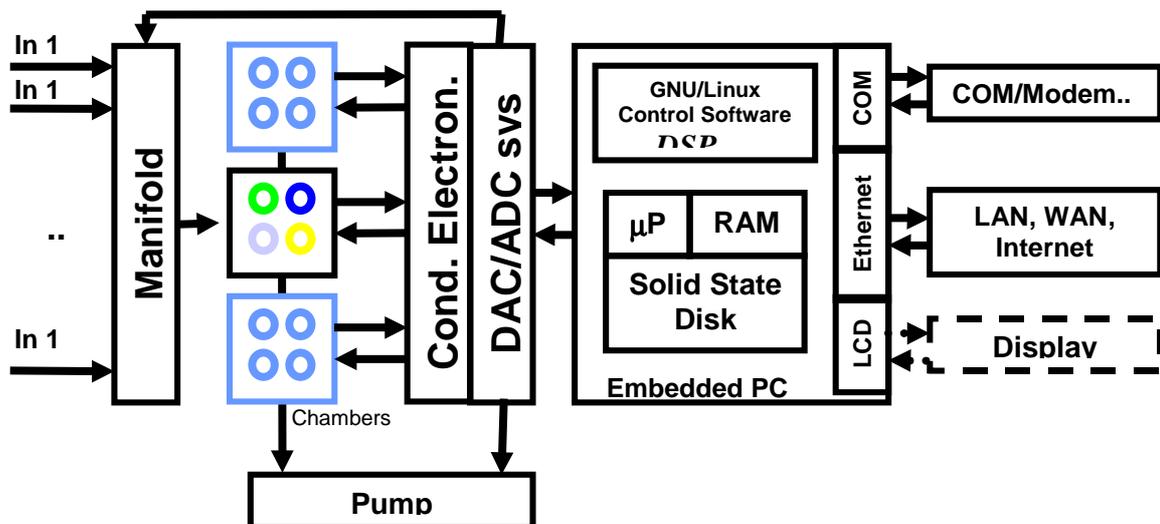


Fig 2. ipNose system overview

possibility is to set up the instrument to phone a remote host computer with the help of a modem, permitting the system to work in remote sites. The inverse scheme is allowed as well, and the instrument can accept incoming phone calls to generate analysis reports

Instrument Design

An overview of the design is shown in fig. 2. The instrument can control up to three sensor modules. Each module consists of four metal oxide sensors, one temperature sensor, and signal conditioning/excitation electronics on a custom printed circuit board (PCB). The sensors and a stainless steel chamber are mounted directly onto the PCB. The electronics can interface various commercial sensors, including FIS, FIGARO, MICROSENS, MICS or CAPTEUR via configuration jumpers, although in the current prototype only FIS sensors are used. These sensors (SB series) present an internal structure based on a micro-bead of sensing material deposited over a coil. This structure provides the sensors with a fast thermal response to a modulating heater voltage, a very practical feature for the purpose of increasing sample throughput.

The flow injection system consists of a multi-channel manifold with one electro-valve for each intake port. The software controls both the order and the aperture time of each valve and the pump, as defined in a configuration file. The reference channel includes a zero-filter for air cleaning. The output of the manifold connects directly to the sensor chamber. The system operates in a vacuum mode by means of a miniature pump connected downstream for the sensor chamber. A check valve is placed between the chamber and the pump to prevent backflow.

The embedded computer represents the core of the system. A PC/104 data-acquisition module is used for acquiring the signals of the sensors and generate excitation waveforms. A separate relay module is responsible for driving the pump and the solenoid valves. The use of a Linux open source operating system provides the instrument with classical UNIX features like multitasking, shared libraries, TCP/IP networking or even multi-user capabilities. Configuration parameters for the

instrument are stored in internal text files. These configuration files allow the user to define various parameters, including the number and duration of the cycles, sampling rates, cycle configuration (pumps, valves, PWM channels...), and arbitrary heating profiles. The use of high-end computing hardware allows complex multivariate analysis of high-dimensional patterns such as those typical of temperature-modulated metal-oxide sensors. Arbitrary temperature profiles can be easily programmed or uploaded into the system as text files (e.g., generated with MATLAB). An example of a particular programmed feature extraction and square heating profile is shown in fig 3. The use of solid-state hard drives allows the system to be used as a huge capacity smell logger, a

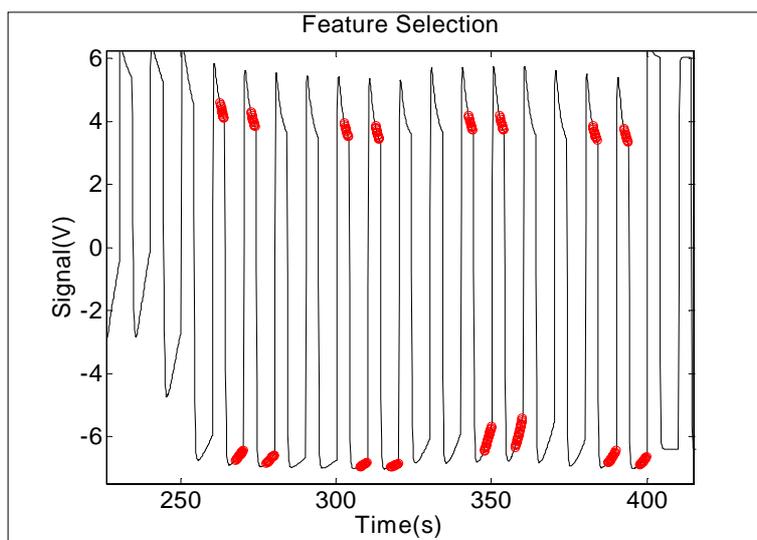


Fig 3. Pulsed Modulation feature extraction example in ipNose

portable intelligent volatile detector or a smell/data-acquisition instrument for processing data in the laboratory.

3 Landfill preliminary data

In following section a test is done in order to evaluate feasibility of an array of commercial metal oxide sensors for landfill site mal odour detection. Results presented correspond to application of gaussian mixture model [MCLA88] computed against FIGARO sensors array data. The aim of this section is to study the feasibility of remote bad odour detectors in landfill sites with the signal processing available in ipNose. This is a non trivial problem as long as any in-field instrument has to suffer strong environmental conditions that will surely introduce strong variability in sensor array signals.



Fig 4 Experimental set up picture

Experimental Set up

Here, dataset gently provided by FUL was collected during week at the end of July and three days at beginning of August. All measurements were taken from 9 am to 18 pm. Also assessment made by the operator nose and values coming from CH₄ and H₂S analysers are provided with data. Some meteorological conditions are measured, like wind speed, wind direction, rainfall, temperature and atmospheric pressure in a weather station.

Electronic nose, gas analysers and weather station are locate in the same shelter at the periphery of the landfill, 10 meters far from the selective odour sources in the East direction. Target odours are biogas odour and waste odour.

The electronic nose used is an array of six Figaro sensors placed in a tight metal enclosure (16x5cm). Electronics provide temperature lectures at two points inside the chamber by means of thermistors (NTC type). One sensor is located inside and the other one is located outside sensor chamber. Both electronic nose and gas analysers collect ambient air from 3.5 meters high PFA tubing. Only operator nose smells in the shelter. The electronic nose cycle is as follows: reference air coming from a Tedlar bag is taken among 5 minutes, and ambient air sampled during another 5 minutes at 150ml/min. Tedlar bags contained odourless synthetic air, filled at laboratory. Some data (last 14 samples) were obtained without regeneration with pure air prior measurement.

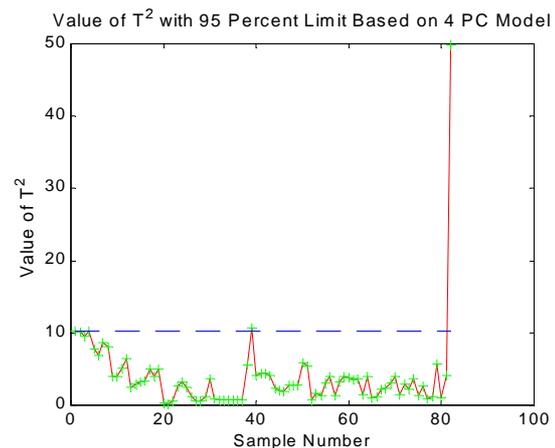


Fig. 5 Hotelling confidence statistics for dataset

Data Analysis

We build features dataset using all six sensor signals and two temperatures. A first sight to data distribution is done by means of PCA, showing that most information is contained in the first five components as shown in table II.

Table I Percentage Variance Captured by PCA. All data

Principal Component Number	% Variance Captured	% Variance Captured Total
1	60.59	60.59
2	24.30	84.88
3	11.02	95.90
4	2.34	98.24
5	1.21	99.45
6	0.30	99.75
7	0.22	99.97
8	0.03	100.00

As shown in fig. 6, where T^2 are plotted values against confidence limit we observe that there is a severe outlier corresponding to last sample. This sample is manually removed although T^2 defines a distance measure of the sample to multivariate mean, and thus, within PCA plane.

The distribution of data after removing the outlier is show in scores plot, fig 7. It can be seen that although some data is homogeneously distributed like biogas samples, waste odour is somehow confused with odourless air. To show the behaviour of GMM over this dataset we also plot the distribution that would be created when using two principal components (84% variance captured). A picture of the component distribution can be also observed in fig 6b.

Data is mean centred, scaled to unit variance and PCA is used as first step to slightly reduce the dimensionality of sensor space to a $d=5$ dimension space. The optimum number of components d is determined with help of leave-one-out cross validation, as shown in fig. 6. Top classification performance (86.4% in training set) is found when including all sensor resistance values and both temperature sensors and in feature space.

A significant dependence of GMM performance with the number of principal components is found. This is a normal phenomena related to the peaking phenomenon [JAIN87] and could be improved using discriminant analysis instead of principal

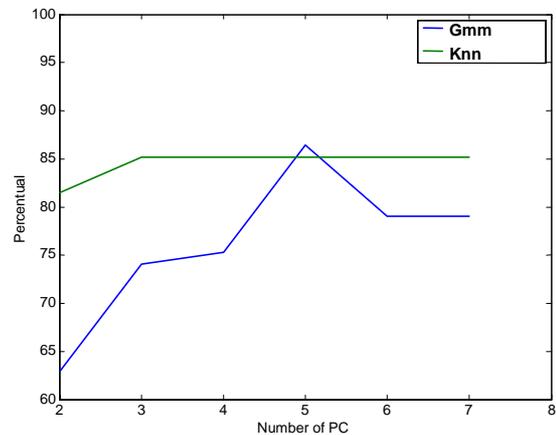


Fig. 6 Classifier performance with validation data (leave one out)

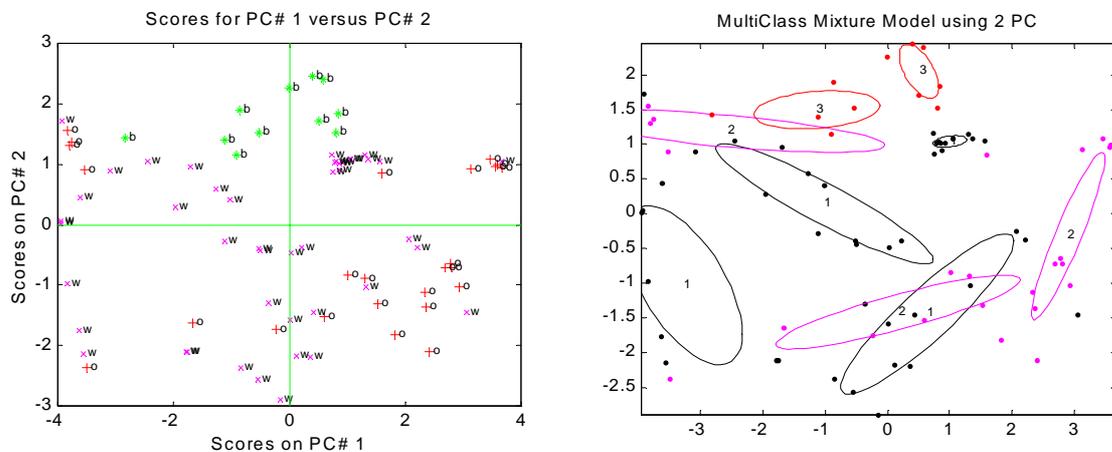


Fig. 7 PCA Score Plot for 2 principal components and corresponding mixture model

component analysis as dimensionality reduction step.
Resulting confusion matrix for leave one out validation is shown in table II.

Table II Confusion Matrix for landfill data(VS=Validation Set, TS=Training Set)

	<i>3-NN (VR=85.1%, TR=88.9%)</i>			<i>GMM (VR=86.4%, TR=91.3%)</i>		
<i>Predicted\Real</i>	<i>Waste</i>	<i>Odourless</i>	<i>BioGas</i>	<i>Waste</i>	<i>Odourless</i>	<i>BioGas</i>
<i>(VS)Waste</i>	38	4	1	42	6	2
<i>(VS)Odourless</i>	6	21	0	3	19	0
<i>(VS)BioGas</i>	1	0	10	0	0	9
<i>(TS)Waste</i>	40	4	1	38	2	0
<i>(TS)Odourless</i>	3	21	0	6	23	0
<i>(TS)BioGas</i>	1	0	10	0	0	11

Note that although results are similar the resources necessary to calculate the EM loop both in memory and computationally are quite lower than for K-nn. Using K-nn we are forced to have all data table in memory while using a Mixture Model only an easy parametric set of normal distributions is held on memory.

4 Conclusions

An exploration of the landfill malodour detection problem is done. Preliminary test using six commercial metal oxide sensors shows that on-field discrimination of biogas and waste odour can be done with signal processing available in ipNose instrument. Mixture models predict a multi-modal probability density function which adapts reasonably to the variability produced by wind direction, temperature and humidity variation. Further work will comprise real remote test using ipNose and temperature modulation techniques to reduce variability in data.

5 References

- [PER01] A. Perera, R. Gutierrez-Osuna, S. Marco “ipNose: a portable electronic nose based on embedded technology for intensive computation and time dependent signal processing” International Symposium Of Electronic Noses (ISOEN2001) abs. 1082
- [KAL97] E. Kalman, F. Winqvist, I. Lundström “A new pollen detection method based on an electronic nose” Atmospheric environment. Vol. 31 No. 11, (1997) 1715-1719.
- [BYU97] H. G. Byun, K. C. Persaud, S. M. Khaffaf, P. J. Hobbs, T. H. Misselbrook “Application of unsupervised clustering methods to the assessment of malodour in agriculture using an array of conducting polymer odour sensors” Computers and Electronics in Agriculture 17 (1997) 233-247
- [ROM00] A. C. Romain, J. Nicolas, V. Wiertz, J. Maternova, P. André “Use of simple tin oxide sensors array to identify five malodours collected in the field” Sensors and Actuators B 62 (2000) 73-79
- [MAG00] N. Magan, P. Evans “Volatiles as an indicator of fungal activity and differentiation between species, and the potential use of electronic nose technology for early detection of grain spoilage” J. of Stored Products Research 36 (2000) 319-340
- [JON97] A. Jonsson, F. Winqvist, J. Schnürer, H. Sundgre, I. Lunström “Electronic nose for microbial quality classification of grains” Int. Journal of Food Microbiology 35 (1997) 187-193
- [MCLA88] McLachlan G. J., and Basford K. E. “Mixture Models: Inference and Applications to Clustering.” New York: Marcel Dekker, 1988