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Odour discrimination from wastewater treatment plants with a portable electronic nose

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A home-made and home-developed electronic nose based on a non-specific array of tin oxide sensors was built in order to discriminate among odors from wastewater treatment plants. The prototype uses headspace sampling system: the headspace of samples of water stored in 15 ml vials is carried out to the sensors cell using an integrated pump controlled by the PC. It also uses an integrated multisensor in silicon composed by six tin oxide gas sensors with different geometries and operating at different temperatures between 400 and 500ºC. The measurement system is based on an USB data acquisition card and an electronic card designed for this application and controlled by pc with a program executed on it. The sensor responses from the six sensor array were stored on the PC and preprocessed for further analysis. Later, linear methods like PCA and non linear ones like Artificial Neural Networks were used to check the discrimination capability of the system. Different samples of water polluted by several typical contaminants have been used to evaluate the performance of the sensory system. Other set of samples coming from different stages of a wastewater treatment plants has been also measured. Results show a complete discrimination in PCA plot and a success rate near to 100% is obtained with Artificial Neural Networks in the classification of samples.

1. Introduction

Wastewater treatment plant operators have long been faced with the lack of suitable sensors and measurement systems for monitoring of wastewater quality. Wastewater that arrives at a municipal sewage works is highly variable in nature and the influent to be treated can be of different origins, such as domestic and industrial sewage and surface run-off. Intermittent or accidental discharge of chemical pollutants and toxic substances into the sewers can have a damaging effect on the bioprocesses involved in treating wastewater. Consequently, polluted waters have the potential to pass through a treatment works untreated and reach the receiving waters where they can have a harmful effect on the environment and threaten drinking water abstraction points down the river.

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Traditionally, wastewater treatment plant operators monitor the quality of the effluent at the outlet of the treatment works using global parameters, such as biological oxygen demand (BOD), chemical oxygen demand (COD), total organic carbon (TOC) and total suspended solids (TSS) (Olsson 1999, Thomas 1997 and Cecile 1998). In addition to providing vital information on the quality of the effluent and treatment efficiency, these procedures demonstrate that a wastewater treatment plant meets statutory discharge requirements (Bourgeois 2001). These procedures are mainly based on sample collection and retrospective laboratory analysis, which are resource consuming and do not facilitate early warning of process failure. Additionally, they cannot provide a high resolution picture of the nature and variations in wastewater quality and expose companies to the risk of undetected incidents. Despite the increasing range and diversity of techniques available, on-line measurement systems have generally remained limited by environmental factors, short lifetimes and fouling problems, mainly because of the harsh environment in which they have to be located. The objectives of the present study were to design and investigate the potential use of a portable electronic nose to monitor the headspace volatiles in water samples generated in laboratory and from the different stages of a real water treatment plant.

2. Material and Methods

2.1 Samples

Two different samples have been measured with the e-nose: water adulterated with pollutants and real water samples from a Waste Water Treatment (WWT) plant.

Adulterated water

In order to check the discrimination capability of the system, several test samples have been prepared with typical domestic pollutants of water. In this way, several samples are prepared containing turpentine, diesel, ammonia, oil, washing powder and petrol. The concentrations of these pollutants are close to the human recognition threshold concentration for that substances.

Wastewater Treatment plant samples.

The wastewater treatment plant studied is located in Arroyo de San Serván, a small village near Badajoz (Spain), and treats municipal wastewater, with only minor contributions from industrial discharges. The treated flow is in average 83.33 m3/day and the plant was designed for 8000 persons equivalent operated for the removal of organic matter, nitrification-denitrification and enhanced biological phosphorous removal using alternated aerobic/anoxic and anaerobic process with extended aeration systems. The WWT plant includes a completely mixed reactor with 2404 m^3 and a secondary clarifier. The system is operated with a sludge age of 20 days and a hydraulic retention time of 15 hours (in steady state).
In an extended aeration system, sewage is brought into a biological basin where is degraded by naturally occurring bacteria. After an “extended” period of time, 15 hours

of detention time, the mixed liquor is sent to a clarifier where it is allowed to settle. Secondary effluent is drawn off the clarifier and the settled biomass is returned to the head of the plant. To maintain a constant mixed liquor concentration, a certain amount of the settled biomass is wasted out of the plant.

The biological basin was provided with mechanical agitators and air diffusers to separate the sludge's mechanical agitation from air supply, and the total air supply time was 8 h per day (1 h/cycle).

In order to obtain significant data, 90 samples were collected over 6 month period and physical–chemical parameters as the total COD, BOD5, ammonia nitrogen concentration, phosphorous concentration and MLSS were measured at the influent of the wastewater treatment plant, effluent of the biologic tank, and finally, at the effluent of WWTP (which in fact is the final effluent) according to APHA (APHA 2001).

Table 1 Characteristics of the wastewater used in this study

Parameter	Influent	Effluent of tank	Effluent of WWTP
Total Solids MLSS (mg/l)	318±25	2720±659	27±5.6
Total Volatile Solids, MLVSS (mg/l)	-	1790±356	-
pH	7.12±0.09	7.23±1.02	7.32±0.06
Chemical Oxygen demand, COD (mg/l)	1443±356	-	17±15
Total Kjeldahl nitrogen TKN (mg/l)	36±12.3	-	4.5±2.36
Total phosphorus (mg/l)	10.6±2.9	-	2.5±2.16

2.2 Electronic nose

An electronic nose is designed and built in our laboratory for water quality analysis purposes. Different features of the system are:

Extraction technique, headspace: To create the headspace the samples of water are kept in a glass vial closed by a septum at constant temperature. To extract the volatile compounds the carrier gas enters by a needle in the septum and exits by another needle. The carrier in the measurements is a flux of 200 ml/min of dry air.

Multisensors: The sensors used (manufactured by Silsens) were metal-oxide sensors deposited over silicon structures that have a heater resistance in the structure. The sensors operate at different temperature in order to improve the selectivity to different gas mixtures.

Device: A portable device should be small, compact, and autonomous. This system is composed by two parts, a laptop and a central control unit. The figure 1 shows a scheme with the parts of the system. The computer executes the software to control the fluidic systems and measures the sensors signal. The fluidic system include electrovalves, humidity filter, pump, electronic circuits to power the pump, electrovalves and heating, resistance, bridges to measure the sensors and electric power source. The control software has been designed in Testpoint ® with a link to a Matlab ® program that allows training a neural network and also using a trained neural network to classify the measurements done in real time.

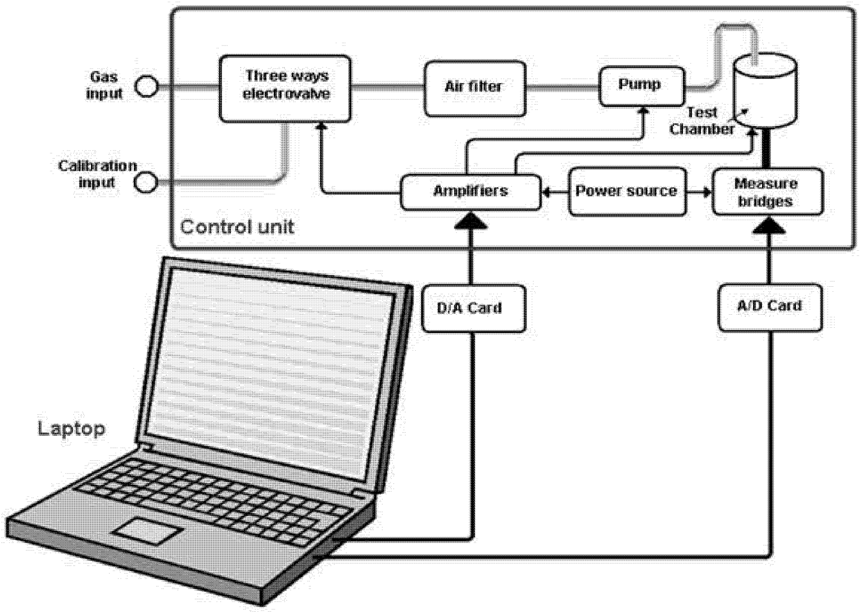

Figure 1: block diagram of the electronic nose.

2.3 Data processing system

The process of data analysis starts after the sensor signals were acquired and stored into the computer. This process can be split into four sequential stages: feature extraction, dimensionality reduction, classification and prediction, and decision making (Gutierrez-Osuna 2002). The first computational stage extracts descriptive parameters from the sensor array response, and prepares the feature vector for further processing. A dimensionality reduction stage projects this initial feature vector onto a lower dimensional space in order to avoid problems associated with high-dimensional, sparse datasets and allow the presentation in 2D or 3D score plot. The resulting low-dimensional feature vector is then used to solve a given prediction problem, typically classification, regression, or clustering. Classification tasks address the problem of identifying an unknown sample as one from a set of previously learned odorants. In regression tasks, the goal is to predict a set of properties (e.g., concentration, quality) for an analyte, typically a complex mixture. In the final step, the recognized class is selected from the previous learned classes or the value of prediction is performed. The selection of models and parameter settings and the estimation of the true error rates for a trained model by means of validation techniques.

One common method for dimensionality reduction is principal component analysis (PCA) (Duda 2001). PCA is a powerful, linear, unsupervised and non-parametric pattern recognition technique that has been used by many researchers to reduce the dimensionality of the pattern space leading to a better visualization of data clustering. One of the most popular supervised methods to handle electronic nose data is the artificial neural network (ANN), which bears a certain resemblance to the function of the human brain. In principle, an ANN is constituted of many (in the order of 50-100) artificial neurons. The artificial neurons are organised in different layers, often three, together forming a network. An artificial neuron is a simple processing element, which in resemblance to biological neurons uses signals from several inputs to produce one output. A linear combination is taken of all the inputs, giving a single value. This value is then used in a transfer function, which could have arbitrary shape. An alternative for classical neural networks are Radial Basis Function Networks (RBFs). They may require more neurons than standard feed-forward backpropagation networks, but often they can be designed in a fraction of the time it takes to train standard feed-forward networks. They work best when many training vectors are available. The learning is very similar to training of odour recognition for humans. After being exposed to an odour only once we seldom remember it very well, while odours we have often experienced in youth can be recognised a long time afterwards. It is important to note that an ANN, just like the human nose, cannot identify odours it has never experienced before. When confronted with the sensor signals from a new odour, the ANN can only say which of the known odours the signals are most similar to, or that it does not recognise the odour.

3. Results and discussion

The measurement data was preprocessed, and after Feature extraction, Principal Component Analysis was performed to the data. Figures 2 show the plot for the two first principal components of adulterated water. It can be noticed that the clusters of the different pollutants are clearly separated. These results are confirmed with the classification with a radial basis function Neural Network, obtaining 100% success rate (percentage of cases correctly classified in validation).

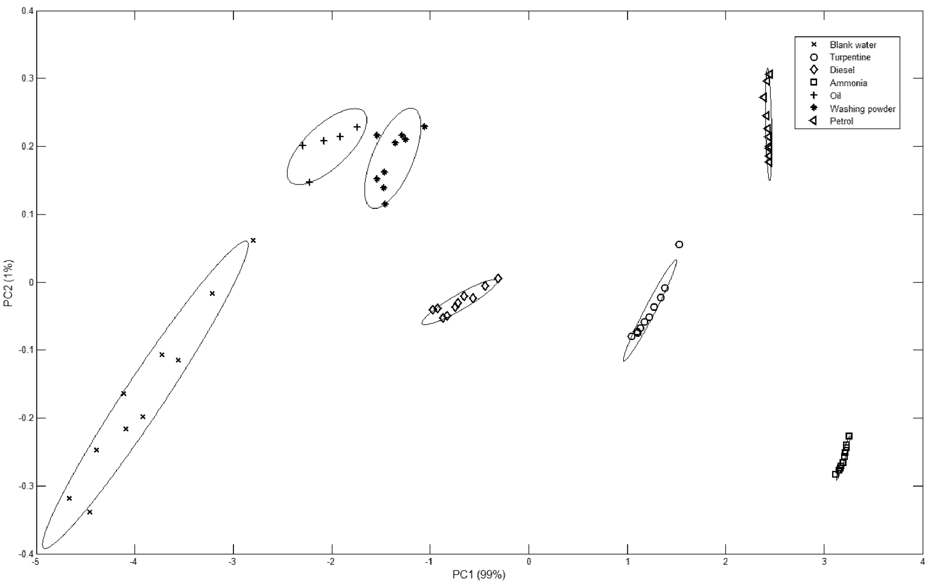

Figure 2: PCA score plot of measurements of adulterated water samples.

The PCA plot of figure 3 show measurements of real water samples from a WWTP. It can be observed partial overlapping between two clusters. This is due to the similarity of this group of samples when they stabilize. The classification of samples from WWTP obtained a 90% success rate with radial basis function Neural Network.

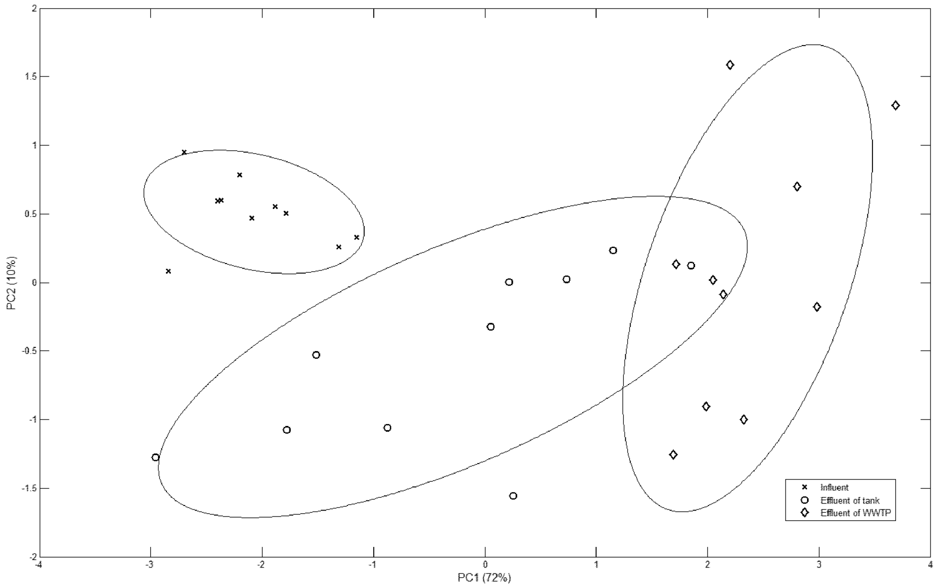

Figure 3: PCA score plot of measurements

It can be concluded the electronic nose could be a useful tool for monitoring waste water treatment plants.

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