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Recent Advances in Electronic Nose and Signal Analysis

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Abstract—*Electronic Nose is a smart system used for identification and quantification of volatile components. The system comprises of an array of gas sensors, which is interfaced with electronic circuits for signal processing and an intelligent pattern analysis system. The sensor responses depend on many variables like the carrier gas concentration, interaction kinetics between the gas molecules and the sensor surface, the sensor surface temperature etc. The limitations of an e nose are related to drift, noise, temperature, repeatability etc. Hence researches are carried out to improve the e nose system performance. This review describes the current development in the sensor technology with special emphasis on some of the statistical procedures used in the analysis of sensor signal analysis. Here initially the design, technology, and sensing mechanisms of different gas sensors are described in brief and then the different procedures adopted for enhancement of electronic nose performance are described.*

1. INTRODUCTION

The design idea of an artificial olfactory system using multisensory gas array was first proposed in 1982 [1]. After that the recent developments in sensor technology, electronics and artificial intelligence leads to the development of smart electronic nose system (e nose) that is capable of identifying, measuring and characterizing volatile component. The term e nose was given in 1988 by Gardner and Barlett who defined it as an instrument which consists of an array of electronic gas sensors and appropriate pattern recognition system capable of recognizing simple or complex volatile components [2]. These types of chemical sensors are able to produce electrical signals that are proportional to the change in some of the chemical or physical parameters of the sensors as the sensors respond in presence of some volatile components [3].

A good gas sensor must have highest sensitivity towards the target volatile components projected for detection.

But it should have relatively low selectivity so that it is sensitive to wide number of volatile components [3]. Its operation involves interaction between volatile components and the sensor coating materials which modulate the electrical signal like changes in current, voltage, resistance etc of the gas sensor, measured by a transducer that converts the modulation into an electrical signal [3]. An electronic nose system consists of 1) a sample injected system, 2) an array of gas sensor as detection system and 3) a data analysis system [4]. Recent advances in e-nose technologies have made possible to use e-nose in wide range of diverse applications including commercial industries, agricultural, cosmetics, environmental, food, manufacturing, military, pharmaceutical, and regulatory sectors, and in many fields of applied science [5].

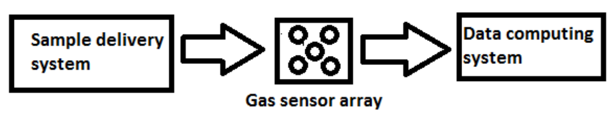

Fig. 1: Electronic nose system

2. SAMPLE DELIVERY SYSTEM

The sample delivery system is used to inject the volatile component into the detection system [6]. To improve the quality of the analysis a cleanup treatment is adopted before and after the volatile component is introduced. In Static headspace extraction method the sample is sealed and a proper temperature is maintained to extract the volatile components from the sample. The extracted part is then injected manually into the gas chamber. It is most widely used as it is easy, simple and inexpensive. But it has low sensitivity [4] and lack reproducibility [6] [7]. In Dynamic headspace extraction method volatile components are extracted from the sample continuously by flowing a gas and that gas is injected into the sensor chamber. In Solid phase microextraction method a fiber coated with absorptive material is used to extract volatile analytes from a sample onto the fiber. Later the fiber is heated to release the sample component into the detection system [4]. The choice of the delivery technique depends on the type of sample used, sensitivity required and the information required.

3. DETECTION SYSTEM - SENSORS TYPES:

Based on the change in conductivity of the MOS or organic polymers due to the interaction of volatile component and the sensor coating material, number of chemosensors is developed.

Metal oxide semiconductor sensors are most widely used gas sensors. The oxide material in MOS sensor contains chemically adsorbed oxygen molecules, which can react with gaseous molecules on the metal oxide surface, and thus alters the surface conductivity. The change in resistance depends on the volatile components that interact with the adsorbed oxygen on the semiconductor [4]. However these metal oxides can be doped with other metals to increase its conductivity [3]. It is inexpensive, robust, and rapidly responsive but generally functions at high temperature 300-500^{0}C and it results in high power consumption.

Metal oxide semiconductor field effect transistor (MOSFET) sensor is based on the principle that volatile components interact with the gate material, leading to the gas molecules diffused through the gate surface and thus alters the threshold voltage of the MOSFET. This interaction depends on the volatile component as well as the material used in the gate of the MOSFET. By changing the gate material and its thickness, porosity of the material used, the sensitivity of the MOSFET sensor can be optimized. But MOSFET sensor undergoes baseline drift [1], [4].

Conducting polymer sensors are made of monomers that are polymerized by chemical and or electrochemical methods. The conducting polymers sensor characteristics are based on measurement of the change in the electrical conductivity when conducting polymers are exposed to volatile compounds. When a gas flows to the sensor, the volatile compounds adhere to its polymer surface and an adsorption desorption process occurs on the polymer layer which alters the electron flow in the system and also the sensor conductivity. Conducting polymers operates at ambient temperature, but their performance get affected by humidity and sensor drift due to oxidation of the polymer over time [4].

The acoustic wave gas sensor uses acoustic wave, measuring the change in wave propagation path. As the acoustic wave propagates through the sensor surface, due to the adsorption of volatile component the velocity and the amplitude of the wave get change. They consist of piezoelectric substrate, hence these devices are small, inexpensive and sensitive to most of the gases. But they suffer from high signal to noise ratio.

The Electrochemical sensor operates on the basis of the reaction of volatile molecules with the catalytic electrode surface. They can operate at room temperature and have low power consumption but they are bulky in size and are highly selective only to a limited number of gases [1],[5].

In optical sensor system, light sources excites the volatile component, producing a signal that can be measured as change in absorbance, fluorescence, polarization, refractive index, interference, scattering, reflectance [4] related to the light signal..

4. PRE-PROCESSING OF SENSOR DATA

The electronic nose produces huge amount of data based on the number of sensor present in the sensor array and the sampling frequency at which it is going to collect the sensor data [6],[7]. It may consist of redundant and irrelevant data. Hence pre processing is always required to remove the redundant data but retaining the original information as much as possible. Three sensor technologies can be identified for signal preprocessing: baseline manipulation, data compression and normalization. All these methods focused mainly on compensation of the drift, extracting informative parameters as features from the sensor array and then preparing the feature vector for further analysis.

4.1 Baseline manipulation

The sensor responses are manipulated with respect to the base line for the purpose of drift compensation, contrast enhancement and scaling. Considering the dynamic response of the sensor the following techniques are normally used. [8]

1. Differential: Here the baseline is removed from the sensor response so that any additive noise or drift present in the sensor signal get removed. Thus base line manipulated sensor response is [5]

   $Y_S\ (t) = X_S\ (t) - X_S\ (0)$

2. Relative: The Relative measurement can be obtained dividing the sensor response by the base line response. It removes the multiplicative drift and a dimensionless response is obtained.

   $Y_S\ (t) = X_S\ (t) / X_S\ (0)$

3. Fractional: The baseline is subtracted and then divided from the sensor response. It is a per unit change with respect to the baseline, which compensates for sensors that have intrinsically large response levels.

   $Y_S\ (t) = (X_S\ (t) - X_S(0)\ ) / X_S\ (0)$

4. Log parameter: This method is useful when the variation of the concentration is very large. The logarithm change in conductance will linearise the sensor output and it will take the value zero in absence of odor input [9] [10].

The choice of the baseline manipulation technique is based on the sensor technology used and the application. However researchers reported [4] that out of all these the fractional change in conductance provides the best pattern recognition performance for MOS gas sensor.

4.2 Compression

The second stage of the pre processing of data is the compression where the huge sensor data has been reduced to a few feature descriptive vectors. The feature vectors are so selected such that they carry the most differential properties without removing the essential information. In most of the cases information is extracted from single parameter when the sensor response reached the steady state, simply neglecting its transient part. But the transient part may also carry information. It has been reported that transient part shows more repeatability than the steady state response. There are many algorithms that can be use for feature extraction from the time dependent sensor response.

1. Steady State: The steady state of the sensor response is considered as feature vector in most of the application [6].

   $Y = R(T)_{MAX}$

But as the transient part may also carry useful information, hence number of different procedures are tried to extract information from the transient part of the response. Three methods have been reported for extracting features from the transient part of the sensor response- the Sub-sampling method, the Parameter-extraction methods and the System-identification methods

2. Sub-sampling method: In this method information is extracted from the dynamic part of the response by sampling the transient part at different time.
3. Parameter-extraction method: This method compresses the transient response by taking the slope, curve integral, rise time, maximum or minimum value [7].
4. System identification method: This method fit a theoretical model to the transient response and then the parameters of the model are taken as the features [7].
5. Exponential curve fitting: It usually shows lossless compression but the computation takes time. Hence sub-sampling and pattern extraction methods are used.

4.3 Normalization

Normalization methods are used to avoid the experimental variation and it will reduce the computation error. Here the values are scaled to readjust the sensor responses to an equal basis. The following methods are normally used

1. Vector normalization: Here example vector is divided by its Euclidean norm so that it lies in a hyper sphere of unit radius.

   $Y = R / (\sum R^2)^{1/2}$

2. Sensor scaling: Here the feature vectors are adjusted so that its co ordinates have zero mean and unit variance.

   $Y = (R - \bar{R}) / \delta_R$, mean $\bar{R}$ and standard deviation δ_R per sample.

3. Dimension auto scaling: Each dimension is normalized so that it has zero mean and unit variance.

$Y = (R - \bar{R}) / \delta_R$, $\bar{R}$ is the mean and δ_R is the standard deviation per dimension.

5. DATA ANALYSIS

The pre processed output data of the e-nose sensors have to be analyzed further to provide useful information. Commercially available analysis techniques fall into three main categories [1]:

1. Graphical analysis:
2. Multivariate data analyses (MDA):
3. Network analyses: artificial neural network (ANN) and radial basis function (RBF)

5.1 Graphical analysis

The graphical analysis is the simplest form of analysis. In this analysis samples or sensor output of unknown analytes are visually compared to those of known source as reference. But if the reference numbers are more, then the analysis process becomes complicated. Graphical analysis can be done using bar chart, profile, polar and offset polar plots etc.

5.2 Multivariate Data Analysis (MDA)

The pre processed and normalized sensor responses are not suitable for further processing due to its high dimensionality and redundancy [7]. Hence dimensional reduction stages are required in feature extraction. It reduces high dimensionality in a multivariate problem and displayed it into smaller dimension. Number of methods is there for dimensional reduction like principal component analysis (PCA), canonical discriminate analysis (CDA) and cluster analysis (CA) etc

The mapping methods are used to find a low dimensional vector which preserves most of the information of the original signal [8]. Most of the mapping methods are linear method. These can be divided into two parts- Supervised and unsupervised procedure. In supervised method, an unknown volatile component is tested and classified comparing it with the known classes. Whereas unsupervised methods separates the different classes from the response class without providing its class descriptions.

1. Principal Component Analysis (PCA): It is a linear unsupervised technique in which projections are generated along the directions of maximum variance. These are defined by the first Eigen vectors of the covariance matrix of the sensor output signal. PCA selects T that minimizes the mean squared distance between original data and those reconstructed from the reduced data [8].

   $T_{PCA} = U \Lambda^{-1/2}$

Where U and Λ are the Eigen vectors matrix and the diagonal Eigen value matrix of the data covariance matrix. PCA is often used as a visualizing tool to represent the multidimensional feature in 2-3 dimensional space.

2. Linear discriminate analysis (LDA): LDA is a signal classification technique, which directly maximizes the class separability and generates projections in the direction where the example of each class form compact clusters. The different clusters are projected far from each other. The LDA transform matrix is given by [8]

   $T_{LDA} = S_W \Lambda_W^{-1/2} S_B$

Where S_W and Λ_W are respectively the Eigen vector matrix and Eigen value matrix of the within class scatter W. S_B is the eigenvector matrix of the between class scatter B.

3. Blind Source Separation (BSS) and Independent Component Analysis (ICA) : Here the original feature vector x is extracted from the sensor array, which can be considered as a linear mixture of sources[8] as

   $X = MM_S$

Where MM_S is the mixing matrix.

4. Canonical Discriminate Analysis (CDA) : Canonical discriminate analysis is a dimension-reduction technique that is related to principal component analysis and canonical correlation. It derives canonical variables (linear combinations of the interval variables) that summarize between-class variations like PCA.

5. Cluster Analysis: The cluster analysis is done by grouping a set of objects in such a way that objects in the same group (known as a cluster) are more similar (in some sense or another) to each other than to those in other groups. There are numerous ways the clusters can be formed.

The hierarchical cluster analysis method is based on distance or similarity between the data. Whereas in k-means algorithm k numbers of clusters are formed and the object is assigned to the cluster for which its distance to the cluster mean is the smallest.

5.3. Network Analysis

1. The artificial neural network (ANN): It is the most popular analysis techniques used for commercially-available electronic noses. It contains interconnected data processing algorithms that always work in parallel.[11],[12],[13]. The algorithms look for similarities and differences between the unidentified elements with the known patterns found in a reference library. The result of ANN data analysis is in the form of percentage matching of identification of the unknown sample with those of referenced one.

Multilayer perceptron classifier is a another classifier where the input is first transformed using a known non-linear transformation. Then this transformation projects the input data into space where it becomes linearly separable. This intermediate layer is referred to as a **hidden layer**. The number of such hidden layer can also be increased. It is a most popular type of artificial neural networks, which works like that of biological neuronal circuitry.[14],[15].

2. Radial Basis Function Network: Radial basis function network is an artificial neural network which uses radial basis functions as activation functions. The output of the network is a linear combination of radial basis functions of the inputs and the neuron parameters. These are feed forward connectionist architectures consisting of a hidden layer of radial kernels and an output layer or linear neurons [7].

6. CONCLUSION

The gas sensors available in the market along with the different analysis technology are briefly reviewed in this paper. Newly developed technologies have provided means to enhance the performance of the smart e nose. The dependency of e-nose performance on various operating conditions like temperature, humidity, operating voltage and its frequency, concentration of analytes are also investigated and reported. A carefully selected sensor system, signal conditioning as well as signal preprocessing is very much essential for achieving optimal performance in e-nose system. The outcome of all these studies will definitely lead to the development of a smart e nose system which will mould the future commercial market.

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