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Electronic Nose: Feature Extraction and their Applications

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***Abstract:** An electronic nose is "an instrument which comprises an array of electronic chemical sensors with partial specificity and an appropriate pattern recognition system capable of recognising simple or complex odours". It can be regarded as a modular system comprising a set of active materials which detect the odour, associated sensors which transduces the chemical quantity into electrical signals, followed by appropriate signal conditioning and processing to classify known odours or identify unknown odours.*

Research has been carried out into the use of thin and thick film semiconducting (inorganic and organic) materials for odour sensing. The research effort is now centered upon the use of arrays of metal oxide and conducting polymer odour sensors. The latter is particularly exciting because their molecular structure can be engineered for a particular odour-sensing application. The electronic nose finds wide applications in the food industry. Future developments in the use of hybrid micro sensor arrays and the development of adaptive artificial neural networking techniques will lead to superior electronic noses.

The perception of volatile compounds by the human nose is of great importance in evaluating the quality of foods. Therefore, it is not surprising that repeated efforts have been made over the years to introduce instruments operating on a similar principle as the human nose: the "electronic nose" is an instrument that encloses the human sensitivity to the objectivity of the instrumental response and supplies results similar to the human nose and in short time.

***Keywords:** Odour, Volatile Organic compounds (VOCs), Sampling, FSS, Carbon Monoxide, Odorant Molecules, Turbinates.*

I. INTRODUCTION

In addition, sensor response and recovery times 10 to 100 times faster than currently available are required for many high-volume applications, such as screening vehicles for explosives, drugs, and other contraband. The new arrays of detectors must also achieve long-term sensor stability, deviating less than 5 percent in their lifetime, as well as device-to-device repeatability.

Otherwise it would be impossible for signal-processing databases (compiled over time during normal operation of the electronic nose system) to fill in as sensors are replaced in the normal course of maintenance.

As these databases for individual electronic nose systems mature, they may be unified into standard application-specific odorant databases. Their general availability will open the way to new ideas in information processing--using information theory to rank each sensor in the array for its contribution to assigned pattern-classification tasks. Then sensors with little to contribute can be eliminated from the array, cutting costs and improving system reliability. For some food applications, the electronic nose will soon be augmented by an electronic tongue.

It could employ the same system building blocks, except that liquid instead of gas sample handling would be involved, and the sensor array would operate in a liquid environment. Early work on this has begun in Japan, where researchers are trying to build an electronic tongue that can identify sweet, sour, bitter, salty, and monosodium glutamate tastes. The systems have been used in quality control for producing beer, coffee, milk, tomato juice, and bottled water.

So in a few years, when you awake in the morning, your coffee maker's electronic nose and tongue may have produced that perfect cup of coffee, the one you enjoy above all others in the universe.

Why to have an electronic replacement of the nose?

Enter the gas sensors of the electronic nose. This speedy, reliable new technology undertakes

What till now has been impossible--continuous real-time monitoring of odour at specific sites in the field over hours, days, weeks, or even months?

An electronic device can also circumvent many other problems associated with the use of human panels. Individual variability, adaptation (becoming less sensitive during prolonged exposure), fatigue, infections, mental state, subjectivity, and exposure to hazardous compounds all come to mind. In effect, the electronic nose can create odour-exposure profiles beyond the capabilities of the human panel or GC/MS measurement techniques.

The electronic nose is a system consisting of three functional components that operate serially on an odorant sample--a sample handler, an array of gas sensors, and a signal-processing system. The output of the electronic nose can be the identity of the odorant, an estimate of the concentration of the odorant, or the characteristic properties of the odour as might be perceived by a human.

Fundamental to the artificial nose is the idea that each sensor in the array has different sensitivity. For example, odorant No. 1 may produce a high response in one sensor and lower responses in others, whereas odorant No. 2 might produce high readings for sensors other than the one that "took" to odorant No. 1. What is important is that the pattern of response across the sensors is distinct for different odorants. This distinguishability allows the system to identify an unknown odour from the pattern of sensor responses. Each sensor in the array has a unique response profile to the spectrum of odorants under test. The pattern of response across all sensors in the array is used to identify and/or characterize the odour.

II. LITERATURE SURVEY

In order to construct replacement of human apparatus like nose, ears etc. researchers have identified distinct steps that characterize the way humans smell. The human perception of odors begins with sniffing, which brings air samples that contain odorant molecules past curved bony structures in the nose called turbinate's.

These turbinates create turbulent airflow patterns that carry the mixture of volatile compounds to the thin mucus coating of the nose's olfactory epithelium, where ends of the nerve cells that sense odorants show up Fig. 1.

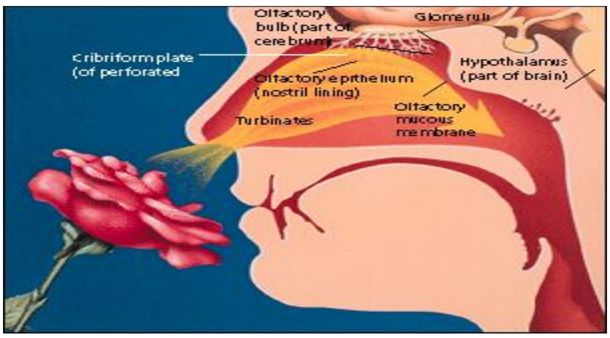

Fig 1

These last create turbulent airflow patterns that allow the mixture of volatile organic compounds (VOCs) to reach a thin mucus layer coating the olfactory epithelium. The sensory cells for detecting odorants are part of the epithelium.

Basic Information on Pollutants and Sources of Indoor Air Pollution

- ✓ Asbestos
- ✓ Biological Pollutants
- ✓ Carbon Monoxide (CO)
- ✓ Formaldehyde/Pressed Wood Products
- ✓ Lead (Pb)
- ✓ Nitrogen Dioxide (NO2)
- ✓ Pesticides
- ✓ Radon (Rn)
- ✓ Respirable Particles
- ✓ Second hand Smoke/ Environmental Tobacco Smoke
- ✓ Stoves, Heaters, Fireplaces, and Chimneys

Carbon monoxide (CO) which is a colorless, odorless gas that interferes with the delivery of oxygen throughout the body. Carbon monoxide causes headaches, dizziness, weakness, nausea, and even death.

Nitrogen dioxide (NO_2) which is a colorless, odorless gas that causes eye, nose and throat irritation, shortness of breath, and an increased risk of respiratory infection.

Volatile organic compounds (VOCs) are emitted as gases from certain solids or liquids. VOCs include a variety of chemicals, some of which may have short- and long-term adverse health effects. Concentrations of many VOCs are consistently higher indoors (up to ten times higher) than outdoors. VOCs are emitted by a wide array of products numbering in the thousands. Examples include: paints and lacquers, paint strippers, cleaning supplies, pesticides, building materials and furnishings, office equipment such as copiers and printers, correction fluids and carbonless copy paper, graphics and craft materials including glues and adhesives, permanent markers, and photographic solutions.

Organic chemicals are widely used as ingredients in household products. Paints, varnishes, and wax all contain organic solvents, as do many cleaning, disinfecting, cosmetic, degreasing, and hobby products. Fuels are made up of organic chemicals. All of these products can release organic compounds while you are using them, and, to some degree, when they are stored.

EPA's Office of Research and Development's "Total Exposure Assessment Methodology (TEAM) Study" (Volumes I through IV, completed in 1985) found levels of about a dozen common organic pollutants to be 2 to 5 times higher inside homes than outside, regardless of whether the homes were located in rural or highly industrial areas. TEAM studies indicated that while people are using products containing organic chemicals, they can expose themselves and others to very high pollutant levels, and elevated concentrations can persist in the air long after the activity is completed.

III. Working Principle

The electronic nose was developed in order to mimic human olfaction that functions as a non-seperative mechanism: i.e. an odour / flavour is perceived as a global fingerprint. Essentially the instrument consists of head space sampling, sensor array, and pattern recognition modules, to generate signal pattern that are used for characterizing odours.

Electronic noses include three major parts: a sample delivery system, a detection system, a computing system.

The sample delivery system enables the generation of the headspace (volatile compounds) of a sample, which is the fraction analysed. The system then injects this headspace into the detection system of the electronic nose. The sample delivery system is essential to guarantee constant operating conditions.

The detection system, which consists of a sensor set, is the "reactive" part of the instrument. When in contact with volatile compounds, the sensors react, which means they experience a change of electrical properties.

In most electronic noses, each sensor is sensitive to all volatile molecules but each in their specific way. However, in bio-electronic noses, receptor proteins which respond to specific odour molecules are used. Most electronic noses use sensor arrays that react to volatile compounds on contact: the adsorption of volatile compounds on the sensor surface causes a physical change of the sensor. A specific response is recorded by the electronic interface transforming the signal into a digital value. The recorded data are then computed based on statistical models.

The most commonly used sensors for electronic noses include **Metal Oxide Semiconductor (MOSFET)** devices - a transistor used for amplifying or switching electronic signals. This works on the principle that molecules entering the sensor area will be charged either positively or negatively, which should have a direct effect on the electric field inside the MOSFET. Thus, introducing each additional charged particle will directly affect the transistor in a unique way, producing a change in the MOSFET signal that can then be interpreted by pattern recognition computer systems, so essentially each detectable molecule will have its own unique signal for a computer system to interpret conducting polymers - organic polymers that conduct electricity **quartz crystal microbalance -** a way of measuring mass per unit area by measuring the change in frequency of a quartz crystal resonator. This can be stored in a database and used for future reference surface acoustic wave (SAW) - a class of micro electro-mechanical systems (MEMS) which rely on the modulation of surface acoustic waves to sense a physical phenomenon. Some devices combine multiple sensor types in a single device, for example polymer coated QCMs. The independent information leads to vastly more sensitive and efficient devices. **General Approach of feature selection;** Bio-electronic noses use olfactory receptors - proteins cloned from biological organisms, e.g. humans that bind to specific odour molecules. One group has developed a bio-electronic nose that mimics the signalling systems used by the human nose to perceive odours at a very high sensitivity: femtomolar concentrations.

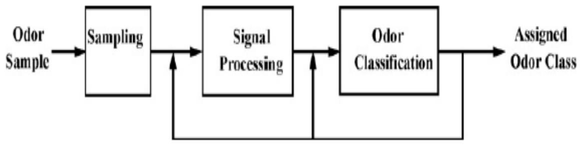

Fig. 2. Typical block diagram of the e-noses.

Typically, the performance of an e-nose is highly dependent on the features being forwarded from the signal processing unit to the odour classification algorithm. If different odour classes give rise to clearly distinguishable patterns, then a high classification performance can be achieved from a simple odour classifier .However, some of the features obtained from an array of sensors are redundant and irrelevant due to cross-sensitivity and odour characteristics.

To mitigate this problem, the chosen sensors must be robust to noise and must have different sensitivity and selectivity profiles among themselves over the range of target odour application. Consequently, machine learning, in general, and pattern recognition, specifically, may be employed to find ways to select only informative features and remove irrelevant features before they are transferred to the odour classification unit. Over the past decade, many researchers have developed a number of feature selection techniques for choosing a near-optimal subset from the originally generated features. This process is called feature subset selection (FSS). The simplest method is to evaluate each combination of the features individually using specific criteria (e.g. maximum classification performance, minimum cost, and/or minimum execution time) and select those with the best performance.

However, this approach is too computationally expensive, and most of the time it is impractical due to limited memory resources. Although, smarter FSS techniques have been developed, brute force processing of e-noses features with high dimensionality and redundant data is now possible in machine olfaction research due to recent advances in computer technologies. In this study, a novel efficient method is proposed by selecting the first few critical sensors based on a maximum margin criterion among different odor classes. Then, a stochastic search algorithm, a genetic algorithm (GA), uses those features as an initial step to optimize our sensor selection process. Note that the features used in this implementation are generated and extracted by applying multilevel wavelet decomposition over dynamic sensor responses.

Feature subset selection (FSS):

Feature selection is considered one of great importance issues in pattern classification, machine learning, and data mining applications. Impressive performance gains have been reported by numerous researchers.

The main reason for optimizing the number of features is not only to extract the relevant features for the pattern classification task but also to reduce the dimensionality of the feature space. One needs exponentially many patterns to completely sample the feature space. Having a large number of features tends to degrade the classification performance. Moreover, most pattern classification algorithms can provide better performance using a subset of the original features rather than the whole set [6]. Therefore, an approach for selecting optimal features and reducing the dimensionality is indispensable in classification problem. In general, there are two terms that are used interchangeably to describe the dimensionality reduction: feature subset selection (FSS) and feature extraction. Feature extraction is a method Fig. 3, Flowchart of a general procedure of FSS. That create new features by manipulating on the original features (y = f(x): Rd→Rm) where m< d while FSS refers to algorithms which choose a feature subset of size m from the original feature set of size d. In this study, we use multilevel decomposition of the sensors' transient responses as our feature extractor, then sequentially supply those sensor features to choose the best sensor subset. The general procedure of FSS is shown in Fig. 2 and it performs as follows. In the first step, a set of candidate subsets from original features is produced by a subset generation unit. This step is regarded as the most important task in FSS since it generates candidate subsets to be the optimal features. After candidate subsets are generated, each subset is evaluated based on the objective function specified by the target application. Then, the result is compared to the previously identified best feature subset. If a better result from the objective function is found, the new feature subset will be defined as the current best feature subset. In the next step, the stopping criteria are examined to determine whether the process should continue or not. Typical rules commonly used are given as follows: (1) a predefined number of subset features are found. (2) A predefined number of generations are reached. (3) A target value of the objective function is achieved. (4) The value of the objective function has no improvement over a predetermined number of generations. Finally, the identified current best feature subset is validated using unseen samples. Various techniques have been proposed in the literatures that determine the optimal feature subset. A straightforward approach is to examine all possible combinations of the original features (2n combinations, n are number of original features). Although this approach is guaranteed to find the optimal feature subset, it is impractical for computation since the number of all possible combinations grows rapidly with the number of features. For example, suppose we wish to find the number of different combinations N by choosing p features from n original features

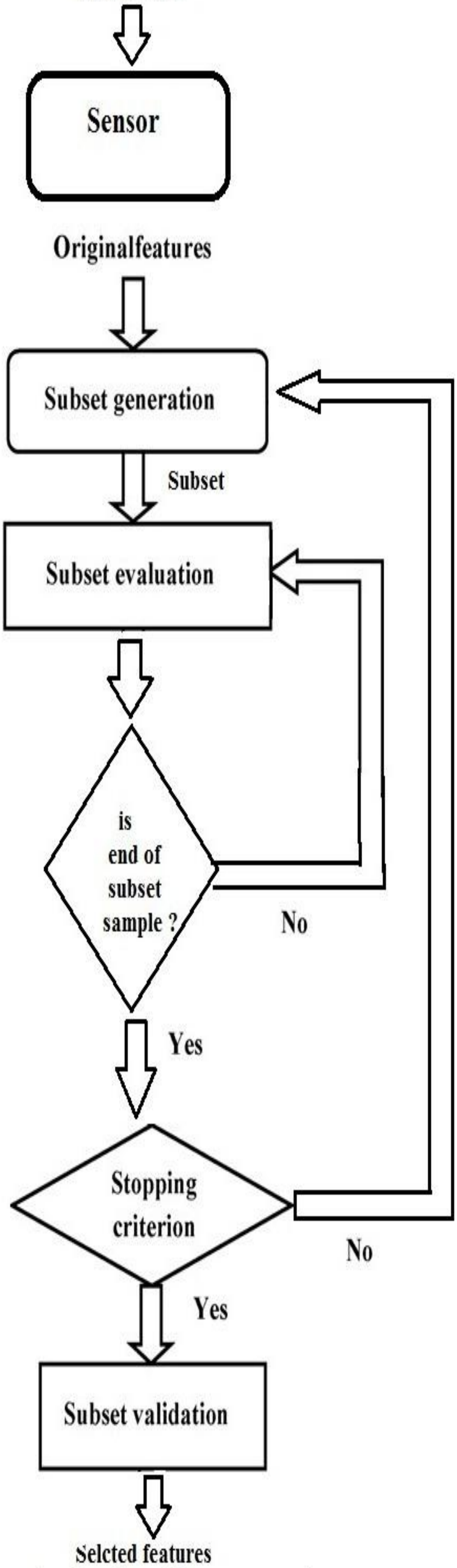

Fig: Flow chart of feature extratraction

We can compute the number of possible combinations N by ignoring p=0 and 1 as shown following equation:

$$N = \sum_{p=2}^{n} \frac{n\,!}{(n-p)!\,p!}, \quad n \geq p$$

Consequently, a heuristic search method is proposed by trading to suboptimal performance in exchange for computational efficiency. The advantage of this method is that we can find the E. optimal solution with a more efficient computation than the complete search (2n). Heuristic search seeks to improve performance by truncating a complete search using special techniques such as Branch and Bound. This method can find the optimal feature subsets without exhaustive search, but the objective function to be evaluated must satisfy the monotonic principle. Another widely used algorithm is a sequential search such as sequential forward search selection (SFS) and sequential backward search selection (SBS). However, both SFS and SBS will only explore a small fraction of the whole combination and can get trapped in local solution. Unlike the sequential strategies in which the features grow or shrink at each generation, the random search method performs a global search from a current population and improves the quality of a population with each pass through the algorithm. This strategy is inspired by evolutionary biology, specifically the widely used genetic algorithm (GA). Although GA is one of the most effective and widely used global search methods, the form of chromosomes (parent population) can be very complex due to the large dimensions of features. Consequently, the optimization process is computationally intensive. Another important issue in FSS is how to determine the “goodness” of a selected feature subset in the subset selection unit as illustrated in Fig. 2. As mentioned, most classification algorithms perform best when relevant features are forwarded to the classifier. While having relevant features is a key to achieve high performance, the definition of a relevant feature is still argued. Kohavi and John [10] originally developed the meaning of relevant features in terms of strong and weak features as follows: First of all, let Xi be a testing feature, Si = {Xi, . . ., Xi−1, Xi+1, . . .,Xn} be the set of all features except Xi, and xi and si be the value assignments to Xi and Si, respectively.

IV. Application

The electronic nose has been used in a variety of applications and could help solve problems in many fields, including food product quality assurance, health care, environmental monitoring, pharmaceuticals, indoor air quality, safety and security, and the military. However, for the electronic nose to succeed in those areas, there need to be marked improvements in technology. The electronic nose can be applied by food manufacturers to such tasks as freshness testing, quality control, and screening of incoming raw materials, not to mention feedback control to optimize bioreactors and minimize batch variation, and monitoring for accidental or intentional contamination or mislabelling of manufactured food products.

V. Conclusion

Humans are not well suited for repetitive tasks. Electronic nose has the potential to become a standard tool for smelling. Researchers are still going on to make electronic nose much more compact than the present one and to make e-nose ICs.

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