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# Computational Parallels between the Biological Olfactory Pathway and its Analogue “The Electronic Nose”: Part II. Sensor-Based Machine Olfaction

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## ABSTRACT

Over the last fifteen years, we have witnessed a rapid expansion in the development of artificial odour sensing systems - or so called “electronic nose” systems. Whilst the power of this approach to flavour analysis has undoubtedly been demonstrated by its recent application to various complex odours, it will be argued that the original research programme, aimed at developing a comparative model of the biological olfactory pathway, has degenerated into an attempt to obtain an *ad hoc* workable system, based around readily available sensor and pattern recognition (PARC) technologies. At the time, the first “model” nose system reflected the limited understanding of sensory information processing carried out within the biological olfactory pathway. We are now presented with an opportunity to evaluate and re-assess the architecture for an electronic nose, in view of the recent advances in understanding the key processing principals exploited by the olfactory bulb and cortex in the identification and characterisation of molecular stimuli.

In Part II of this paper, we examine the parallels that exist between the biological olfactory system and the electronic nose. It is shown that the two systems share many similarities in their architectures and other properties, such as odour delivery, nonspecific sensor/receptor response, sensor/receptor preprocessing and Content Addressable Memory (CAM) function. Of particular importance, both systems need to overcome similar operating problems, such as sensor/receptor drift, degeneration and poisoning, limited sensor/receptor sensitivity, discrimination of odour quality invariant of intensity and also the identification of particular odour components within a mixture of background odours. Finally, a number of opportunities for improving the biological plausibility of electronic nose systems are suggested that may yield an improvement in performance.

Keywords - Biological Olfaction, Artificial Olfaction, Cellular Processing, Biological Computation.

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## 1. Sensor-Based Machine Olfaction

The concept behind the development of odour-sensing systems resulted from progress in a number of key research areas. The first of these was the identification of suitable materials possessing sensitivity to chemicals. One of the earliest studies, carried out by Tanyolac (1953), involved the measurement of changes in surface tension following adsorption of an odorant.<sup>1</sup> With the advent of semiconductor materials, new opportunities for chemically sensitive sensors became available and, as early as 1953, Brattain and Bardeen performed the first preliminary studies on the possibility of a semiconductor chemical sensor.<sup>2</sup> In 1965, the search for chemically sensitive devices continued when Dravnieks carried out a number of studies examining the effects of odours on the contact potentials of various materials.<sup>3</sup> At around this time, one of the first artificial olfactory systems was produced by Wilkens and Hartman (1964), although this was limited in performance. The system relied upon the electrochemical effects of odorants at a number of electrodes.<sup>4</sup>

A second key area of research providing inspiration for an odour sensing system was the modelling of information processing within the olfactory system. This provided the basis for the understanding of the biological domain we have today, as reviewed in Part I of this paper.<sup>5</sup> A seminal work by Deutsch (1967), providing a formal framework for information processing in the olfactory pathway, laid the foundations for a generic “model nose” and the concept of partial specificity of sensor response for odour discrimination.<sup>6</sup> These factors, combined with an interest in learning/classification systems and multi-component gas sensing using arrays of nonspecific chemical sensors (ChemSADs), has contributed to the possibility of electronically sensing odours.

The first “model/electronic” nose, based upon a small chemoelectronic sensor array, was developed some time later in a study by Persaud and Dodd (1982).<sup>7</sup> Although this system comprised only three chemically active sensors, it provided the generic architecture used in most systems today. This architecture, modelled on the limited understanding of the biological olfactory system at that time, and in particular the work of Deutsch, relied upon an array of partially specific sensors and a primitive method of data fusion, able to provide discrimination between a number of simple odorants. The potential for an inexpensive sensor-based system able to solve elementary problems in the food, fragrance

and beverage industry stimulated the whole area of research in artificial olfaction that continues today.

The term “electronic nose” was coined for such systems around the late 1980s and has recently been defined by Gardner and Bartlett (1994) as<sup>8</sup>

*.... an instrument, which comprises of an array of electronic chemical sensors with partial specificity and an appropriate pattern recognition system, capable of recognising simple or complex odours.*

Developing from this definition, it is possible to describe a generic architecture for an electronic nose system - depicted in Fig. 1.1. The system comprises of an odour delivery or sampling system, an array of chemically sensitive sensors with partial specificity to a range of odorants, signal preparation (in the form of sensor and array processors), a pattern recognition (PARC) engine, and some form of odour representation scheme.

[Place Fig. 1.1 Near Here]

As shown, the stimulus to the electronic nose is provided by an odour delivery system. Odours interact with a sensor array - each sensor possessing some form of chemically active material. In the physical system key measurands of sensor response (such as conductance) may be converted into a vector of voltages,  $v_{ij}(t)$ , by interface electronics, forming input into an Analogue to Digital Converter (ADC) stage. Subsequent processing is then performed digitally, usually by a computer: firstly, a sensor processing function may be applied to provide a time-independent metric for each sensor response,  $v'_{ij}$ , and array processing may be applied to perform global scaling and normalisation to form the vector array  $\mathbf{v}''_j$ . These array processed data are then used as input to some form of PARC engine, which uses a knowledge base of previously encountered odour “fingerprints” in order to classify or transform the overall pattern of array responses into some form of odour representation. Systems often provide an output predictor in the form of a 1-of- $k$  classification. However, these outputs may also provide the scalar variables making up an odour space that could be used to describe the stimulus according to a suitable set of descriptors or odour terminology system as will be discussed later in Section 6.

It is the focus of this paper, to provide a comparison between the model of the biological system (as discussed in Part I of this paper<sup>5</sup>) and the architecture of the electronic nose (as

shown in Fig. 1.1). In both systems it is the pattern of activation across the array of sensors that is of importance, as each sensing element possesses partial specificity to a wide range of odorants. Also, massive convergence at the first stage of processing in the biological system is reflected in the use of data reduction techniques (such as Principal Component Analysis [PCA]) for exploratory data analysis in the electronic nose. In both systems this processing allows an opportunity for a reduction in the dimensionality of the sensory data, providing a more defined sub-space. After data reduction, both systems achieve their function of odour recognition through the use of some form of associative memory for the storage and recall of previously encountered odours. In the biological system this is achieved by the Central Nervous System (CNS), and in particular the piriform cortex (as discussed in Part I of this paper<sup>5</sup>) whilst the pattern recognition engine combined with a knowledge base provides this in the electronic analogue. These as well as other parallels will be considered more closely as we examine the chemoreception and processing layers of the electronic nose in turn.

## **2. Odour Sensor Technologies**

### **2.1. Odour Sensors for use in an Electronic Nose**

Since early studies on chemically sensitive materials we now have a wide variety of sensor technologies suitable for electronic nose systems. A number of requirements for these sensor technologies are listed in Table 2.1. In contrast to the ideal gas sensor, which should be highly specific to a single chemical species, sensors for use in a electronic nose system need to possess partial specificity, demonstrating similar “broadly tuned” responses to olfactory receptors in the nose (as discussed in Part I of this paper<sup>5</sup>).

[Place Table 2.1 Near Here]

Such ensemble sensor characteristics ensure that it is the entire pattern of response across the sensor array that provides odour quality information, rather than the response of any one particular sensor. These partial specificities of the sensor elements forming the array also need to be overlapping, but not identical in response so as to provide a high informational content to the first stage of processing. This is evident from the observation

that a number of sensors responding identically within an array clearly provides little or no additional information to that of a single sensor.

Sensor elements also need to show fast (at least in the range of seconds to minutes), reproducible, and reversible responses to odorants. Devices with response times slower than a number of minutes are unlikely to be suitable for on-line commercial electronic nose systems. Reproducible sensor response requires that the sensor signal will not vary significantly under repeated test stimulus - clearly of vital importance to any system encountering the same odour over a period of time. Reversible response requires that sensors need to possess good recovery properties after exposure to an analyte. This provides a stable registration point before each odour measurement from which a response metric can be formally defined ( $v'_{ij}$  in Fig. 1.1). The "off" recovery time will often be as critical as the "on" response time in defining the suitability of the sensor, since this parameter limits the period required between tests for required for recovery.

The following desirable properties of odour sensors ease the design and implementation of an electronic nose instrument. For example, monotonic near-linear sensor responses to increasing analyte concentrations obviate the requirement for linearising techniques, particular pre-processing methods or complex non-linear pattern recognition techniques such as Artificial Neural Networks (ANN). Sensors that have stable response characteristics, subject to only a small amount of baseline drift, simplify the task of pattern recognition as well as extending the useful life of calibration data-sets that form the knowledge base of the system. Furthermore, sensors that differentiate well between molecular stereochemical properties should also provide good discrimination when used within an electronic nose. Ideal properties for a future portable odour monitoring instrument might include small device size - allowing small sample volumes and large sensor arrays, low power consumption so as to conserve battery power and ease of sensor fabrication.<sup>9</sup> Finally low sensor noise ensures good data integrity and so provides a corresponding improvement in the reproducibility of response.

[Place Table 2.2 Near Here]

Clearly then, sensors for use in an electronic nose have to meet a number of requirements. These can only be satisfied by fine control over the large number of parameters involved in sensor fabrication. Table 2.2 provides a comprehensive survey of the electronic

nose systems developed to date, classified according to sensor array type, and including details of each system such as the number of sensing channels used, the choice of sensor and array pre-processing, type of pattern recognition technique employed and those applications that have been investigated. The table has been necessarily been restricted to systems conforming to the electronic nose definition provided above. As shown, a number of competing sensor technologies are currently used in electronic nose systems and these can be compared for some of the essential, desirable and ideal properties. These include Metal Oxide Semiconductor (MOS) devices, conducting polymers, piezoelectric devices, Metal-Insulator Semiconductor Field Effect Transistors (MISFETs) and electrochemical cells.

## **2.2. Comparisons with Olfactory Receptors**

All of the odour sensing technologies used in electronic nose systems possess the first essential requirement of partial specificity towards odorants. In the biological system, overlapping partial specificity at the receptor level of the olfactory pathway clearly provides a high degree of redundancy within the system (see Part I of this paper<sup>5</sup>). This redundancy provides a number of potential benefits. Firstly, a signal of high information content is provided to the first stage of processing, so that the system can suffer massive trauma and still operate effectively. Evidence for this is provided by cases where the removal of large sections of the olfactory bulb have only resulted in restricted perception of odour intensity as opposed to affecting the overall range of odours that can be appreciated. Secondly, Shepherd (1991) has argued that redundancy through overlapping response spectra of the receptors allows the discrimination of odour quality independent of its intensity (as outlined in Part I of this paper<sup>5</sup>).<sup>64</sup> Thirdly, the biological system is in a prepared state for a wide range of stimuli, both familiar and unfamiliar, since the non-specific characteristics of the receptors ensure that as broad as possible sampling of the odour space is taken. This provides the olfactory sense with a highly desirable xenobiotic quality that is essential in an environment where there is little correlation between one olfactory stimulus and the next (over time). That is, the next odour cannot be predicted and may not even be familiar.<sup>65</sup> Given such unknown operating constraints the inverse method of biological implementation, as it were, where highly specific receptors are used by the nose seems

untenable since the system would need to generate a new receptor class for each newly encountered odour. Such an arrangement would be difficult to envisage in evolutionary terms. It is suggested that the high number of overlapping receptor classes is exploited by the biological olfactory system to implement the processing principles listed above.

Comparable partial specificity of odour sensors within the electronic nose provides similar benefits of high informational content (providing a degree of fault tolerance) and also xenobiotic capability (an array comprising sufficient numbers of broadly tuned elements is responsive to a whole range of odours not considered at the design stage, or maybe even discovered yet). These benefits result directly from adopting a similar processing architecture to the biological system. However, the use of partially specific sensors for the discrimination of odour quality, independent of intensity, has not yet been considered. Further investigation on mimicking this neural mechanism may be of direct benefit to future electronic nose systems.

[Place Table 2.3 Near Here]

Some operating properties of electronic nose sensor technologies and olfactory receptors are compared in Table 2.3. The partial specificity of the device can be judged by the Molecular Receptive Range (MRR) given in the table. For all the devices this is wide, although the insensitivity of SnO<sub>2</sub> semiconductor sensors to nitrogen- and sulphur-based organic compounds narrows this range considerably. Importantly, all forms of device, both hardware and wetware, show some form of intensity coding (i.e. the key measurand changes in response to a particular odour, up to the point of saturation. This was discussed for olfactory neurons through the use of the electro-olfactogram (EOG) in Part I) and this is, of course, a primary requirement of any odour sensor. Perhaps not surprisingly, it is clear that the fabricated odour sensors have an inferior operating specification when compared with their biological counterpart, the olfactory neuron. For example, olfactory neurons possess a much faster response time (as discussed in Part I) in comparison with odour sensors (20–60 s), and this is a limiting time factor in the response of any artificial odour sensing system. Also, olfactory receptors require far less power, and although the relatively high power requirements of artificial devices is not currently an issue in existing electronic noses (since today these generally employ less than 50 sensors) it will become a critical factor as array sizes become larger, and portable instruments are also developed. Clearly

physical device size will then also become important and integrated devices will become increasingly necessary.

Ironically, all of these sensing units are destroyed (after gradual deterioration) during operation, and are also susceptible to poisoning by interferences such as particular chemical species and over-exposure. This is a technical aspect of electronic nose design that clearly limits the application of the instrument to repeated odour monitoring. As discussed in Part I of this paper, the biological system copes with this degeneration by continually replacing olfactory neurons, whilst having massive stocks of receptors of each type operating at any one time.<sup>5</sup> It seems likely that massive convergence of output from olfactory receptors forming a single class onto a single glomeruli structure may provide a more constant signal in view of this continual neurogenesis. How an electronic nose might benefit from such an arrangement will be discussed later in Section 4.2.

The key measurand of element response is provided by modulation of spiking frequency for olfactory neurons and device resistance in many odour sensors, as verified by EOG measurement on the olfactory epithelium. Schild and Gardner (1991) have proposed that a frequency-based measurement scheme used in the electronic nose may be another method of compensating for degeneration within odour sensors.<sup>67</sup>

Stereochemical properties provide the most sensitive molecular determinant of odour quality, although at least 20 other such determinants or “descriptors” are required for a complete description. For this reason, steric sensitivity in artificial odour sensors is fundamental to the resolving power and MRR of an electronic nose system. From Table 2.3 it is clear that currently only olfactory neurons and conducting polymers possess this important quality, although the use of lipid layers will allow us to design a higher degree of steric sensitivity in the future.

That a high number of different molecular determinants are required to describe odour, suggests a need for electronic noses employing a hybrid of different sensor technologies. In this way, each sensor transduction mechanisms involved could be used to detect different aspects of the same odour molecule. For example, conducting polymers could be used to detect particular functional groups within stimuli; piezoelectric devices could be used to determine molecular mass and provide some steric selectivity through the use of lipid layers; and electrochemical cells with catalytic filaments could be used for determining

relative amounts of pyrolysed components. Such an approach to an electronic nose has not yet been sufficiently investigated, although a promising study using both MISFETs and Taguchi devices has recently been reported by Winqvist *et al.* (1993).<sup>59</sup>

The principles of operation of artificial sensors currently seem far removed from their biological counterparts. There are two different approaches being used to develop biomolecular devices - the use of natural structures (biological) and the use of completely synthesised (biomimetic) structures.<sup>68</sup> Biomimetic sensor materials would provide transduction mechanisms that are more closely modelled on their biological counterparts. The use of natural structures would involve cloning olfactory receptors away from the epithelium. As already discussed in Part I, the work of Buck and Axel (1991) has provided a suitable method for cloning olfactory receptor genes and it has since been shown that olfactory receptors behave identically away from the epithelium.<sup>64,69</sup> Although no electronic nose systems have yet been reported that are based on bioelectronic research these are certain to become more prominent in the future.

### **3. Odour Delivery Systems**

#### **3.1. Static Headspace Analyser**

Unfortunately, the non-specific response of many odour sensors can also be affected by a number of physical variables in addition to odours. An important function of the odour delivery system is to control these factors, ensuring that the system responds only to the odour under investigation.

To date, many electronic nose systems have relied on simple static based odour delivery, where odours are introduced manually into a closed vessel containing the sensor array. In the seminal work by Persaud and Dodd (1982), a static headspace analysis of odours was carried out using an array of three TGS sensors, housed in a sealed glass flask and odours were introduced by injection using a Hamilton syringe. Under such conditions the injected analyte completely vaporises, forming an odorous headspace to which the sensor array responds. Since this study, static headspace analysis has become the most common method of odour delivery within electronic nose systems and has been chosen by many workers. For example, Shurmer *et al.* (1990),<sup>11</sup> Gardner *et al.* (1990)<sup>70</sup> and

Yokoyama and Ebisawa (1993)<sup>54</sup> have all employed such an approach. Although this form of odour delivery system provides a quick method of analysis, it lacks reproducibility (due to experimental errors introduced by a human operator) and is also time consuming on account of being manually intensive. These systems have largely been developed in order to obtain a working system and bear little relationship to odour delivery within the biological system.

### **3.2. Flow Injection Analyser**

Flow based odour delivery to an electronic nose system has been achieved by developing automated Flow Injection Analysis (FIA) systems. Up until recently, systems for FIA work have been primarily developed for gas sensor characterisation and multi-component gas sensing using ChemSADs. Similar to odour sensor arrays, ChemSADs can display sensitivity to a number of physical variables other than odour, such as sampling temperature, sampling humidity, sensor head pressure and sample flow rate. Using an FIA system many of these physical variables as well as other testing parameters can be directly controlled, or at least monitored thereby permitting parametric compensation.

[Place Fig. 3.1 Near Here]

A small number of FIA systems have also been developed as part of electronic nose systems, similar in design to the system shown in Fig. 3.1. In general, the number of testing variables and parameters in odour sensing is far higher than in multi-component gas sensing using ChemSADs. These might include odour carrier gases, bubbling or non-bubbling sampling methods, time required to reach headspace equilibrium in addition to those already identified for ChemSADs above. Consequently, a higher degree of control over the testing procedure is required. This can be achieved using FIA based odour delivery systems. Furthermore, microcomputer control of the sampling procedure can provide rapid sampling as well as reduce the experimental co-efficient of variation from one sample to the next.

Odour delivery within the biological olfactory system, on the other hand, must also maintain a high degree of control over undesirable physical variables such as sample flow, temperature and humidity. Odour delivery is flow-based in the form of repetitive odour pulses or “sniffs” (as discussed in Part I of this paper<sup>5</sup>) . As a result of the complex

aerodynamics of the nasal cavity, air flow to the epithelium is presented in a controlled, repeatable manner, although subsequent neural processing must also take into account some variation. Furthermore, receptor temperature is controlled by internal homeostasis and humidity levels are maintained by the deployment of receptors within a mucus membrane. Clearly then, FIA based electronic nose systems mimic similar operating conditions to those present in the biological system and are therefore likely to be necessary for reliable odour measurement.

Flow-based odour delivery in the biological system is combined with a complex form of physical segregation effected by the mucosal layer of the epithelium (as discussed in Part I of this paper<sup>5</sup>). This segregation allows for an initial sorting of molecules (by molecular mass) to different portions of the receptor sheet. In this way receptors with a particular affinity for certain types of odour can maximise their chemoreception through optimising their physical location on the receptor sheet. How such segregation might be usefully employed within the electronic nose has not yet been fully investigated, although the combination of Gas Chromatographic-Electronic Nose (GC-EN) instrument that can be used for measuring complex odours has recently been considered.

An interesting aspect of odours is that an odorant and its source are not necessarily chemically identical. As Gibson (1966) points out, “the odour of a source specifies it but it is not chemically identical with it”.<sup>71</sup> This effect is clearly demonstrated in a complex mixture of molecular species, where diffusion in an open environment will take place at differing rates depending upon the molecular mass of each species. This leads to relative concentration differences between each of the components in space and time, causing the quality of the overall stimulus to change. Shurmer and Whitehouse (1993) have recently considered this aspect of odorants.<sup>72</sup> They agree that, “the very idea of smell being an intrinsic property of a substance, and as such being sensed by a receiver, is false. It has a temporal, spatial, human equation which is demonstrated by anyone’s experience”. Importantly, they highlight the need to consider such effects for odour measurement, since it may not be possible to devise suitable standards against which to compare complex odours (similar to Standard Temperature and Pressure [STP]). It will not be possible to develop a comprehensive performance definition for electronic nose systems until such odour standards have been developed.<sup>73</sup> In terms of the odour delivery system for an

electronic nose, such a diffusion effect can be minimised using an FIA or combined GC-EN system, since odour transport takes place under forced convection of the headspace during the sampling process. Such considerations are of course paramount to the design of a portable odour sensing instrument.

## 4. Signal Preparation

### 4.1. Sensor Pre-processing

In the electronic analogue, sensor pre-processing is used to condition input data prior to array processing and pattern recognition (as shown in Fig. 1.1). Each sensor,  $i$ , produces a time-dependent signal (such as conductance),  $v_{ij}(t)$ , in response to an odour pulse (of type  $j$ ) impinging upon the array, as shown in Fig. 4.1.

[Place Fig. 4.1 Near Here]

It is often convenient to remove the time-dependence of the signal, by isolating the minimum and maximum values attained both before and after odour stimulation. Using these parameters,  $v_{ij}^{min}$  and  $v_{ij}^{max}$ , respectively, a number of pre-processing metrics,  $v'_{ij}$ , have been applied to odour sensing arrays. Many of these metrics originate from work in gas sensing using metal oxide semiconductor devices

$$v'_{ij} = v_{ij}^{max} - v_{ij}^{min} \quad (4.1)$$

$$v'_{ij} = \frac{v_{ij}^{max}}{v_{ij}^{min}} \quad (4.2)$$

$$v'_{ij} = \frac{v_{ij}^{max} - v_{ij}^{min}}{v_{ij}^{min}} \quad (4.3)$$

$$v'_{ij} = \log_{10} \left( \frac{v_{ij}^{max}}{v_{ij}^{min}} \right) \quad (4.4)$$

These include the difference model, Eq. (4.1), applied by Heiland (1982),<sup>74</sup> relative model, Eq. (4.2), applied by Yannopoulos (1987),<sup>75</sup> and fractional model, Eq. (4.3), applied by Morrison (1982).<sup>76</sup> By removing the time-dependence of the signal, the amount of data to be handled by later stages of processing is reduced, making the recognition task simpler. There have currently been few reports of incorporating transient sensor data as part of

later stages of processing. As is evident from Table 2.2, all of these metrics have been applied to a variety of odour sensing arrays, although it is notable that the difference model has been more widely applied to metal oxide and lipid layer array devices, while the fractional and relative models have been favoured for use with conducting polymer arrays.

The logarithm metric, Eq. (4.4), may be used to linearise sensor response for devices that can be modelled using a power law, such as metal oxide semiconductor sensors. The conductance of a single metal oxide device to  $k$  odour components,  $j$ , can be described by

$$\Delta G_{\infty} = A_0 + A_1 c_1^r + \dots + A_j c_j^r + \dots + A_k c_k^r \quad (4.5)$$

where  $r$  is a constant for the sensor and lies between 0.3 and 0.8, and the coefficients  $A_j$  determine the MRR or specificity of the device. The model assumes that the principle of linear of superposition holds and the effect of the odour components act independently on the sensor. The response of the sensor is seen to be non-linear with increasing odour component concentrations (particularly for high values). This response can be linearised using a logarithm pre-processing metric such as Eq. (4.4). Such a linearising technique may be usefully applied in odour sensing when odour component intensities is of particular importance.

The logarithm metric may also be used when responses to an odour vary considerably across the array, leading to smaller responses being ameliorated during array processing or pattern recognition. In this case the logarithm metric increases the relative contribution of small sensor responses that is presented to later stages of processing and so can aid discrimination. Clearly, the use of the logarithm pre-processing metric increases the overall dynamic range of the system, although this is achieved at the expense of amplifying instrumentation noise.

As reviewed in Part I of this paper, the biological system performs comparable signal conditioning at the glomeruli layer of the olfactory bulb.<sup>5</sup> The logarithm pre-processing metric of the form described by Eq. (4.4) may be mimicking the dynamic range compression of sensory input within the biological system described in Part I.<sup>5</sup> Such compression of sensory input, mediated by a logarithmic transfer function within the bulb, similarly increases the dynamic range of the system. Again, this increase in dynamic range is at the cost of increasing the effect of noise within the system, although as has also been considered, the

biological system compensates for this by averaging of receptor input. This biomimetic pre-processing mechanism has not yet been investigated in electronic nose research.

## 4.2. Array Pre-processing

While the use of sensor pre-processing conditions array data by individually extracting single-valued pre-processing metrics, any form of pattern recognition must consider the response of the complete array to achieve odour discrimination. The response of a sensor array to an odour pulse can be visualised as a curve in sensor space, shown in Fig. 4.2(a).

[Place Fig. 4.2 Near Here]

In general, a point in this sensor space can be described by a column vector of individual sensor responses

$$\mathbf{V} = (v_1, v_2, \dots, v_r, \dots, v_R)^T \quad (4.6)$$

where  $R$  is the number of sensors within the array and so defines the dimensionality of sensor space. At time  $t = t_0$  the array is exposed to an odour pulse, such as the one shown in Fig. 4.1(a). Subsequently, a characteristic time-dependent path is traversed in sensor space that is governed by the partial selectivities of the sensors to the odour stimulus. Finally, after some time  $t = t_{ss}$ , the steady state response of the sensor is obtained (provided that  $t_{ss} \gg t_{90\%}$ ). It is possible to provide a time-independent measure of this response by forming an  $R$ -dimensional Euclidean distance metric, as shown in the figure. This is the simplest metric, being linear, and corresponds to a vectorial representation of the difference sensor pre-processing model described by Eq. (4.1).

In terms of the array response, the effect of using such a difference sensor pre-processing metric, such as Eq. (4.1), to discriminate between two different odours is illustrated by Fig. 4.2(b). The difference metrics corresponding to each odour measurement are grouped at the origin, forming a difference pre-processing space. Assuming that the array is suitable for the odour discrimination task in question, clusters of response vectors may be formed corresponding to different odour classes (as shown). Similar spaces can also be formed for the fractional, relative, and logarithm models, although the relationships between these and sensor space are not as intuitive as for the one shown.

Although the use of sensor pre-processing models may provide the required separation in array response vectors to the different odours under investigation, the range of values

may not be predictable. A scaling technique has been applied by a number of workers in order to confine each sensor response between the range  $[0, 1]$  in order to maximise the coverage of input space into a classifier

$$v''_{ij} = \frac{v'_{ij} - \min_j (v'_{ij})}{\max_j (v'_{ij}) - \min_j (v'_{ij})} \quad (4.7)$$

Often termed sensor normalisation, Eq. (4.7) can be more correctly described as sensor range-scaling or autoscaling (as the lengths of response vectors are not set to unity). This has the effect of linearly scaling each response vector so as to fit inside an  $R$ -dimensional unit-hypercube, as shown in Fig. 4.2(d). It should not, however, aid odour discrimination, since sensor normalisation only sets the gain within the data-set as a whole.<sup>8</sup> Range-scaling is often used in conjunction with neural network methods, so as to make maximal use of the input space. The application of this technique to electronic nose systems is widespread, as shown in Table 2.2.

Normalisation can also be carried out across the sensor array to enhance odour discrimination

$$v''_{ij} = \frac{v'_{ij}}{\sqrt{\sum_{i=1}^{i=R} (v'_{ij})^2}} \quad (4.8)$$

Such array normalisation maps the response vectors onto the surface of a  $R$ -dimensional hypersphere of unit radius, centred at the origin, as shown in Fig. 4.2(c).<sup>33</sup> As a result, the response vectors are set to unit length, in effect removing the concentration dependence within the data. This technique has been widely applied to a variety of sensor array types to promote the identification and discrimination of odours independent of their concentration, such as in a 1-of- $k$  classification scheme. Such a method is not appropriate for odour characterisation, where the intensity of the signal may be of importance, or where very small response vectors may be included within the data-set.

As with the biological system, marked convergence takes place in the electronic nose at the array processor level after sensor pre-processing has been performed (see Fig. 1.1). As discussed in Part I of this paper, the biological olfactory system uses convergence to provide sensitivity enhancement. This sensitivity enhancement derives from an increased

measurement certainty brought about by summing the response from a number of like receptors at the glomeruli, and also by the overlap in the response of different receptor types. Such a technique, whereby the detection limit of the system as a whole is far greater than the detection limit of the individual receptor cells is known as hyperacuity and is a feature of many biological systems. Hyperacuity occurs as a direct benefit from the broad tuning of receptors and consequent redundancy present within the biological system. As already discussed, the increase in Signal to Noise ratio (S/N) depends upon the convergence ratio within the system - so, for humans 1,000 receptor cells synapse onto a single mitral cell to provide a  $\sqrt{1,000}$ , or a 30-fold increase in the S/N ratio at the first stage of processing.

[Place Fig. 4.3 Near Here]

An analogous technique may also be applied to the electronic nose in order to increase the overall sensitivity of the system, as shown in Fig. 4.3. By replicating each sensor of a particular type (each giving an S/N ratio of  $S_D$ ) combined with some form of signal averaging will provide an overall S/N of  $S_D\sqrt{n}$ . This decrease in noise may be directly translated into increased sensitivity at the detection limit of the devices by increasing the forward gain within the system. Such a biomimetic approach to sensitivity enhancement has not yet been applied to electronic nose systems.

Such an arrangement has the added advantage of providing a more stable response in view of continual sensor degeneration, poisoning and drift. The effect of a single degenerative sensor, within the scheme proposed in Fig. 4.3, will be significantly reduced by the signals from the  $(n - 1)$  operative sensors. In combination with a suitable sensor validation scheme, as shown, faulty sensors may then be isolated and replaced, with little effect on the overall characteristics of the odour sensing system.

## 5. Pattern Recognition Techniques

By definition, some form of PARC engine lies at the heart of an electronic nose (according to the definition cited in Section 1). During odour discrimination, using a 1-of- $k$  classification scheme,  $k$  binary output predictors are used to identify one out of  $k$  possible simple or complex odours. Under such a scheme, incoming array data (after suitable sensor and array pre-processing) are compared against a set of known odour prototypes, or “fingerprints”, corresponding to the  $k$  odour classes. These prototypes must be stored within the knowledge base during a learning or training phase. Using a variety of classification techniques it may then be possible to classify the unknown odour according to its fingerprint, into one of the  $k$  classes. Collectively, these stages of processing may be referred to as pattern recognition.

[Place Fig. 5.1 Near Here]

The variety of PARC techniques that have been applied to electronic nose systems are summarised in Fig. 5.1. These have been arranged according to a number of properties that define their suitability for different applications. The techniques naturally split into those used for visualisation of large multivariate data-sets (Visual Exploratory Data Analysis [VEDA]) in terms of just a few key variables and those techniques providing a method to classify data-sets. The range of techniques within each of these categories will be considered below. The particular type of pattern recognition techniques used in different electronic nose systems have been summarised in Table 2.2.

An important property of pattern recognition techniques is whether they undergo supervised or unsupervised learning. This distinction is shown in Fig. 5.1. The pattern recognition methodology that has been described above is a form of supervised learning. This occurs when *a priori* knowledge about the category membership of a set of samples is used to develop a classification rule during a training phase. The purpose of this classification rule is to then predict the category membership for new samples, in a test or operational phase. Examples of supervised pattern recognition techniques applied to electronic nose systems are Principal Component Analysis (PCA) for array data visualisation and the Multi-Layer Perceptron (MLP) for odour class assignment. In contrast, unsupervised learning attempts to discover its own statistical structure present in the data-set

without any *a priori* class assignment. Consequently, such a technique does not require a formal training phase similar to that described for supervised learning. Currently only two unsupervised techniques have been applied to the electronic nose, these being used primarily for data visualisation - Cluster Analysis (CA) and Self-Organising Maps (SOM) or Kohonen networks. While a supervised training regime clearly provides a far more conducive environment for learning, unsupervised learning is more akin to the adaptation that takes place within the biological olfactory system. For an electronic nose instrument operating in the field, repetitive supervised learning via constant re-calibration is not realistic, due to time and economic constraints. A more realistic training procedure may be provided by a combination of both techniques, whereby the system undergoes an initial period of supervised learning, followed by a reduced amount of on-line or unsupervised learning that continues during operation. Such an approach has not yet been exploited in electronic nose systems.

Some pattern recognition techniques (such as those based upon maximum likelihood theory and Bayesian estimation theory) assume known probability distributions of array data. These are termed as parametric techniques and usually require that the data being classified are multi-normal and also linearly independent. Examples of classification techniques subject to these restrictions are the Bayes classifier and least squares based methods, such as linear regression. Often the available data-set under consideration is not large enough to justify the assumptions made by parametric methods, and so their application to odour sensing is often restricted. Non-parametric techniques, on the other hand, make no assumptions about the data being processed. Although these methods may not be as powerful as parametric methods (when the aforementioned assumptions are met), they are not subject to the same restrictions, and so may be more widely applied.

Some techniques may only provide linear mappings between their input and output parameters. These techniques may only be applied when sensor responses are shown to be linear with concentration change (or have been suitably linearised using sensor pre-processing techniques as considered in Section 4.1). Furthermore, the principle of superposition must hold for the combined action of complex odour components. Examples of linear pattern recognition techniques applied to data visualisation are PCA, Euclidean CA,

Feature Weighting (FW) and Discriminant Function Analysis (DFA), and for odour classification K-Nearest Neighbour (K-NN), least squares methods such as linear regression, and the Bayes classifier. Linear PARC techniques also require that the output or target parameters behave linearly with concentration change. This will not be the case when using an electronic nose to predict sensory-like odour descriptors (such as those obtained from a sensory panel). In particular, this is because the psychophysical description of perceived odour intensity is non-linear, being described by Stevens' Power law<sup>77</sup>

$$R = c(I - I_0)^n \quad (5.1)$$

where  $R$  represents perceived odorant intensity as described by the perceiver;  $I$ , physical intensity (odorant concentration);  $I_0$ , an estimate of minimal effective value of the stimulus or stimulus threshold, and  $c$  is a constant of proportionality. Under these circumstances, a pattern recognition technique capable of providing non-linear mapping between the input and output parameters is essential. Examples of non-linear pattern recognition techniques applied to data visualisation are SOM and non-Euclidean CA, and for odour classification are MLP, fuzzy based reasoning and Learning Vector Quantisation (LVQ). This category includes some of the most successfully PARC techniques to be applied to sensor arrays.

### 5.1. Comparison with Biological Information Processing

The pattern recognition techniques considered act as a form of Content-Addressable Memory (CAM) by way of function mapping between various input and output vectors, based upon training examples. Such CAM function is essential to both the artificial and biological systems in their task of odour (object) recognition and discrimination.

The massively parallel architecture of the olfactory bulb and its associated cortex, combined with its impressive ability for odour memory storage and retrieval, clearly suggests that a connectionist or Parallel Distributed Processing (PDP) approach to pattern recognition within the electronic nose may prove beneficial, or at least increase biological plausibility. The first PDP network considered for modelling memory processes occurring in olfaction was the associative memory, as already discussed in Part I of this paper.<sup>5</sup> These models were highlighted as having excellent qualities for odour memory storage and recall, including reproducible pattern activation, generalisation, ability to deal with degraded input as well as good pattern separation. However, the information storage efficiency of

associative memories is abysmally low unless sparse coding of the input data is used. This implies a very large number of inputs, with only a small number of these carrying data at any one time. While such conditions may exist for input to the piriform cortex in the biological system, it will not be the case for sensor array data, where partial specificity of sensors within an array, ensures a high degree of overlap within the data. Fortunately, PDP mapping networks, such as the MLP do not require particularly sparse coding of the input space to operate efficiently, but still carry out heteroassociative CAM function.

Unfortunately, while the MLP as well as many other competing PDP paradigms bear passing resemblance to some aspects of later stages of processing within the biological olfactory pathway, there currently exist many more differences than similarities. In particular, it was clear from the overview of the biological olfactory pathway provided in Part I of this paper that temporal patterning of neuronal activity is just as fundamental as spatial patterning to the way in which sensory information processing is conducted.<sup>5</sup> In fact, oscillation has been considered to be fundamental to processing within the brain for some time.<sup>78</sup> Freeman (1992) has considered the processing within the biological system to rely heavily on the non-linear dynamics of coupled oscillators.<sup>79</sup> According to Freeman, the connectivities of nerve cell assemblies (controlled by the efficacy of the dendro-dendritic synapses between mitral and granule cells) establish the potentiality for multiple trajectories in the dynamic phase space of the olfactory bulb - this being the space of all possible spatio-temporal patterns. Each trajectory may form a stable state of oscillation, although only one of these may be realised at a time. Together, all possible trajectories form a global chaotic attractor in this phase space (analogous to the Lorenz attractor).

While the precise rôle of oscillation in olfactory information processing may be unclear, current connectionist models (such as the MLP) being used to model olfactory processing have only been considered for their static qualities. It is becoming increasingly clear that the initial goal of network stability within connectionist systems may have been a false one, and that far more interesting and useful processing principles will be discovered through consideration of their dynamic properties.<sup>80</sup> Likewise, in sensor-based machine olfaction future consideration of dynamic computational models of the biological olfactory system (such as those highlighted in Part I of this paper<sup>5</sup>) is likely to provide the key to exploiting

information processing that is both biologically more realistic as well as also being invariant to sensor drift and background odour interference.

## 6. Odour Representation

Like any scientific instrument, an electronic nose system must represent measurands to its environment to be of use. As such, some form of odour representation scheme is required in order to reliably communicate measured odour information to the analyst. This is the final component to an electronic nose system as shown in Fig. 1.1.

There are principally two odour representation schemes that can be usefully employed within an electronic nose. Firstly, odour discrimination can be represented in its simplest form by a 1-of- $k$  classification as discussed in Section 5. Such a method has already found application in many odour discrimination tasks (such as in the detection of fake champagne and vintage wines). However, such a scheme will be of limited value when more detailed characterisation of odour quality is needed (as required in, say, identifying taint odour notes within a spoiled beverage or foodstuff).

[Place Fig. 6.1 Near Here]

In this case a second method, where odours may be characterised through the use of a set of organoleptic-like odour descriptors (such as nutty, floral, estery alcoholic etc.) provides more detailed information relating to the stimulus. The lack of sensory primitives in olfaction compounded with difficulties in arriving at a useful set of primary odours,<sup>82</sup> requires that currently the best way to represent odours would be under a flavour terminology system such the flavour wheel for beer, shown in Fig. 6.1. In this way sensor array data from an electronic nose could be mapped onto such a set of flavour terms to provide humanly defined odour information, using PARC techniques combined with supervised learning. Such a training régime can be summarised by Fig. 6.2.

[Place Fig. 6.2 Near Here]

Odour discrimination studies carried out to date using electronic nose systems (as reviewed in Table 2.2) have exclusively applied the first method of odour representation. There are severe limitations associated with this method. As already mentioned, pure odour classification will not provide adequate characterisation of a stimulus *per se*. Furthermore, unless the odour information is represented in human terms, it will not be readily

understandable to an analyst. In order to provide more meaningful and understandable data from future odour sensing systems, the application of the second method of odour representation will need to be explored.

## 7. Concluding Remarks

In Part II of this paper we have considered the architecture underpinning existing electronic nose systems, from odour delivery through to pattern recognition and finally odour representation. A comparison has been made between this information processing architecture and that comprised by the layers of neural processing making up the biological olfactory pathway (considered in Part I). Not surprisingly, clear parallels exist between the two systems that principally derive from the seminal work of Persaud and Dodd in 1982. Their famous paper exploits a rudimentary model of information processing within the olfactory system that was proposed by Deutsch as long ago as 1967. It is clear, with hindsight, that while advances in sensing and computing technology have vastly improved the practical performance of current electronic nose systems, such instruments are still limited by the outmoded model of the biological olfactory processing upon which they are based.

Consequently, this paper evaluates and re-assesses the architecture for electronic nose systems in view of the recent advances in understanding the key processing principals exploited by the olfactory bulb and cortex. In so doing, a number of opportunities for performance enhancement in the practical system have been described. In particular,

- SAR studies in olfaction have been unable to locate a single molecular determinant upon which odour quality depends. Rather, it seems that more than 20 molecular determinants are important in defining odour quality. Consequently, there is a clear argument for using a hybrid of sensor technologies within an electronic nose in order to capture different aspects of the odorant under investigation. Future sensor arrays will need to be specialised to the problem domain in question through an appropriate selection of sensor technologies.

- As considered in Part I of this paper, broadly-tuned overlapping receptor responses provide an ability to discriminate odour quality and quantity (concentration) independently, as a result of subsequent neural processing that emphasises the differential response of similar receptor classes. Such an approach could be exploited to the advantage of the electronic nose.
- Large numbers of classes of receptors within the biological system provide xenobiotic response. That is, the system takes as broad a sample of the odour space as possible and may respond to odorants even though these may not yet have been experienced. This feature will naturally occur in electronic nose systems that comprise sufficiently large stocks of non-specific sensors.
- In the biological system physical segregation of odorants is mediated by the mucosal layer of the epithelium. This provides an initial sorting mechanism to direct functionally distinct classes of odorants to different portions of the receptor sheet. Such an approach might be usefully employed in a hybrid multi-sensor array combined with a GC column. Using such a scheme it would then be possible to direct specific classes of odorants towards the most appropriate sensor technology as odour species elute from the GC column over time.
- Convergence within the biological system has been shown to enhance system sensitivity, through averaging of receptor input, in addition to providing a constant olfactory signal in view of continual receptor degeneration and neurogenesis. An equivalent scheme has been proposed in the electronic analogue that demonstrates these important properties.
- Dynamic range compression of sensory input may be mediated in the electronic nose through the use of the logarithmic preprocessing metric. There is evidence for a similar mechanism in the biological system that improves the overall range of odour concentrations that can be perceived.
- Finally, pattern recognition techniques applied to electronic nose systems have been compared to the associative models of the piriform cortex in the biological system. Advantages in performance in the electronic analogue may be achieved by considering dynamic neural processing, such as computational neuronal models.

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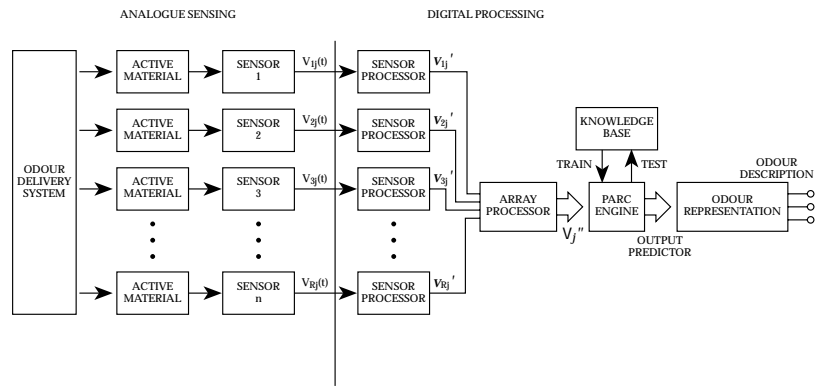
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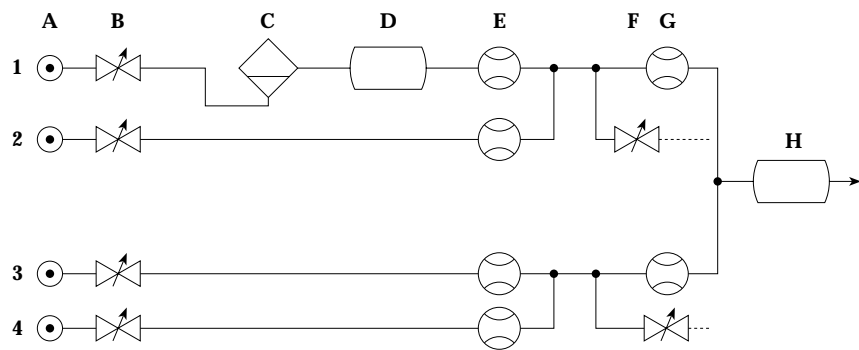
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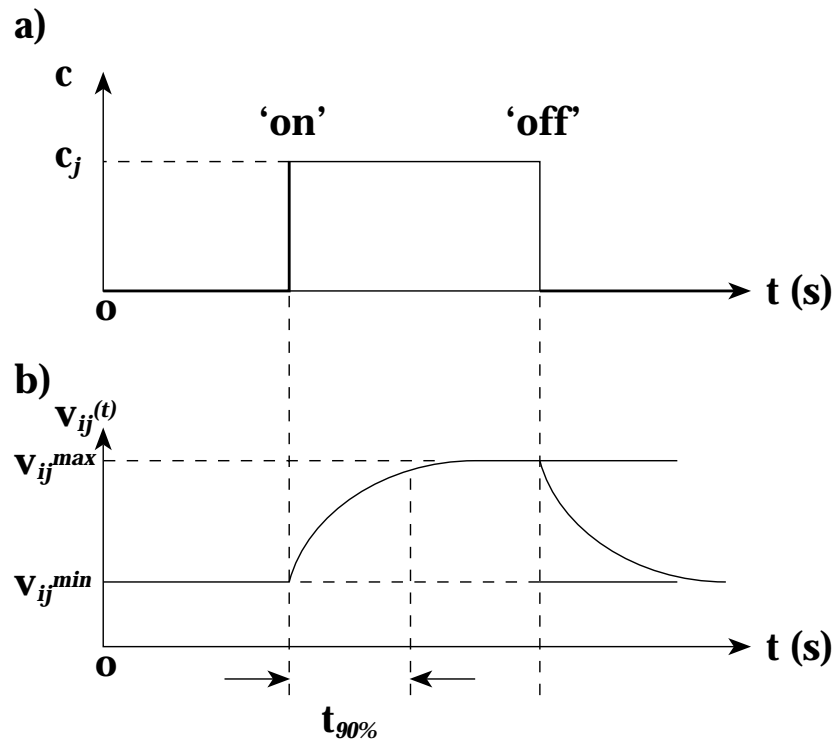
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**Figure 1.1:** Generic architecture of an electronic nose, (Adapted from Gardner and Bartlett [1994]<sup>8</sup>).

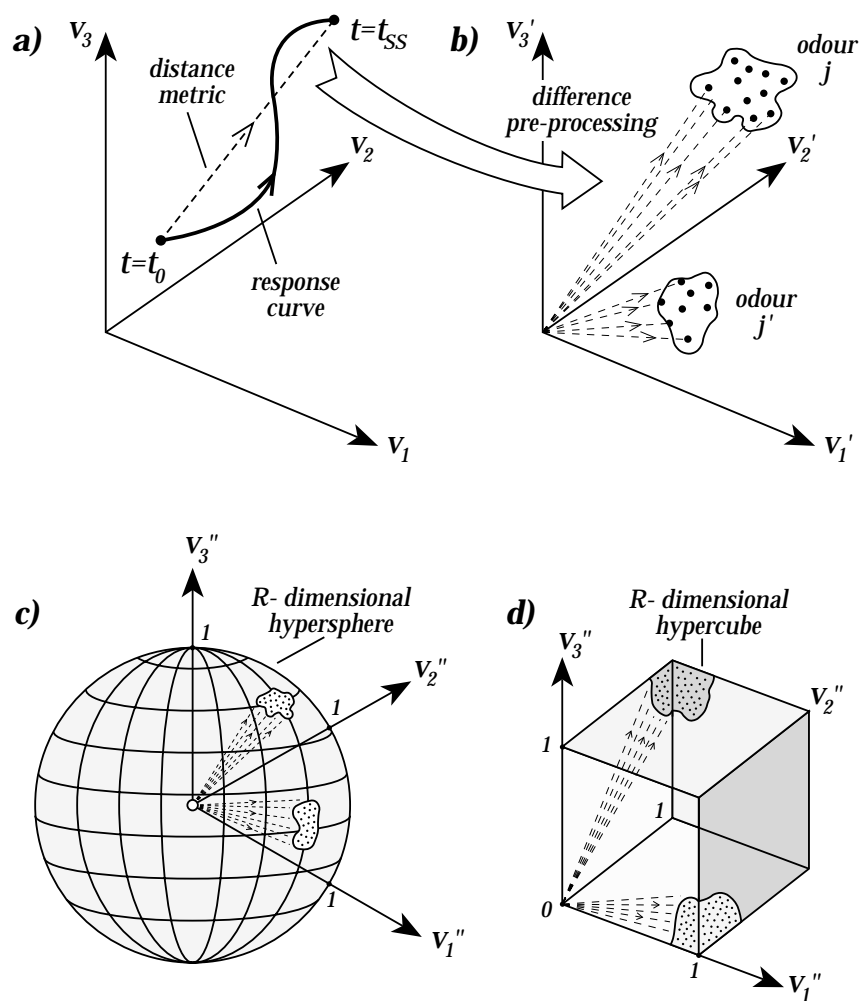


**Figure 3.1:** Schematic Diagram of an FIA analysis system for an automated electronic nose system. From right to left are shown, gas bottle sources (line 1,2 and 3), line filters, Mass-Flow Controllers (MFC), non-return valves, two-way purging valve, quad normally closed (NC) valves, sample vessels, fuel cell with compressor pump, final flow-meter, sensor head bypass valve and sensor head housing temperature, humidity and discrete conducting polymer sensors, (Reprinted from Pearce *et al.* [993]<sup>34</sup>).

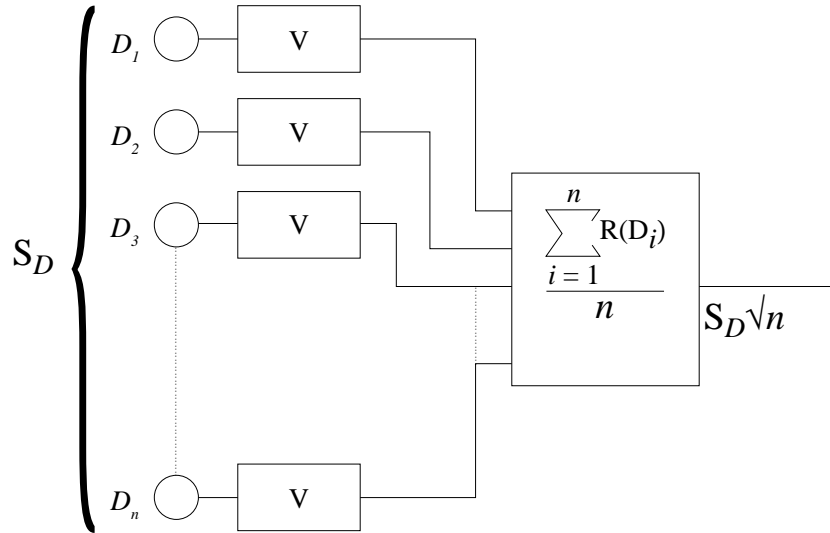


**Figure 4.1:** The response of a single odour sensor to an idealised odour pulse. a) Odour pulse of concentration  $c_j$ . b) Time dependent sensor response,  $v_{ij}(t)$ , showing the pre-processing parameters  $v_{ij}^{min}$  and  $v_{ij}^{max}$ . The rise time for the sensor is given by  $t_{90\%}$ .

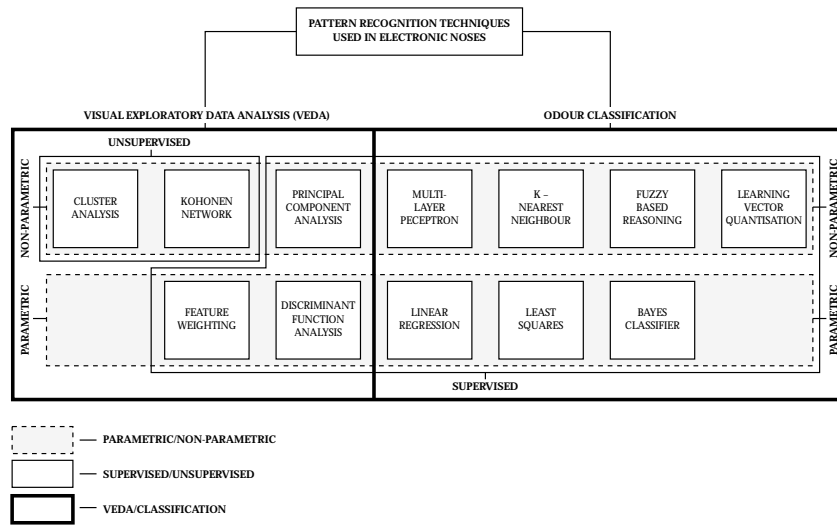
Contents



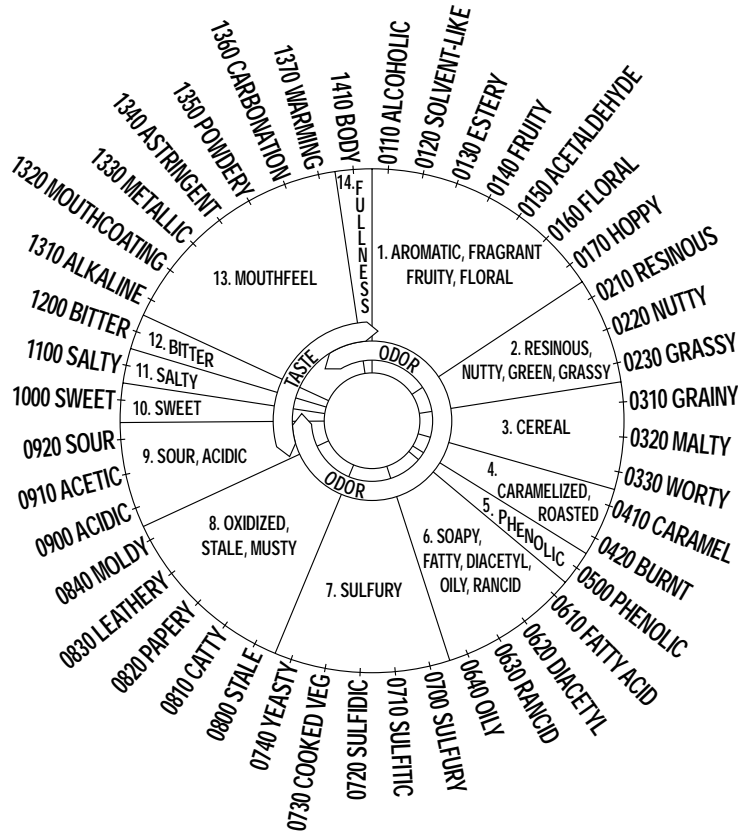
**Figure 4.2:** Representation of the response obtained from a three element odour sensor array in ( $R = 3$ ) dimensional space to an idealised odour pulse. a) Sensor space. b) Difference pre-processing space. c) Array normalisation space. d) Sensor range-scaling space. (See text for description).



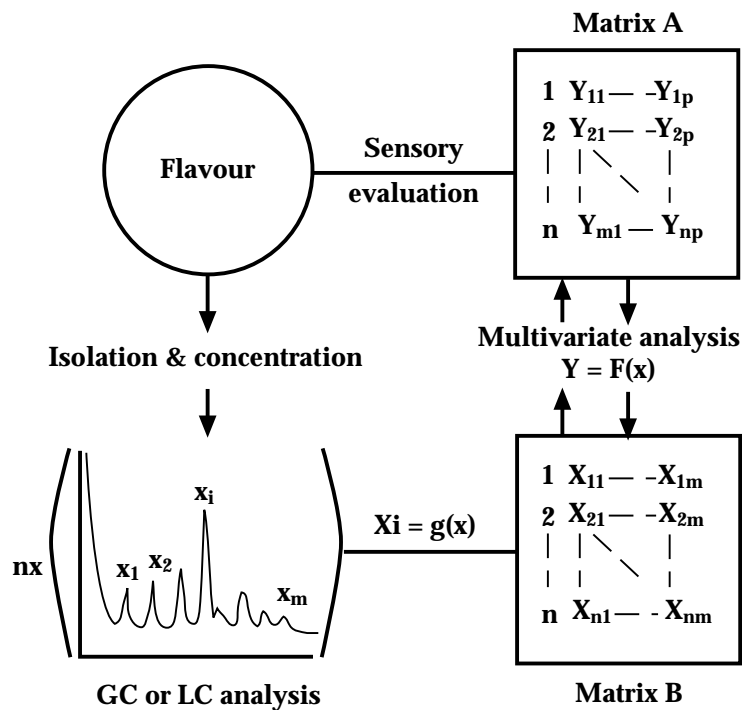
**Figure 4.3:** A drift compensation and sensitivity enhancement scheme for an electronic nose having enhanced noise rejection and good signal stability to sensor degeneration, drift and poisoning. Each sensor,  $D_i$ , of a single type or class is replicated  $n$  times, each having a Signal to Noise (S/N) ratio of  $S_D$ . Signal averaging is performed leading to a more stable sensor signal of S/N ratio  $S_D \sqrt{n}$ . A sensor validation scheme may be used for each sensor to detect failing or poisoned sensors, that may require replacement.



**Figure 5.1:** Summary of pattern recognition techniques applied to electronic nose systems. These have been classified according to Visual Exploratory Display Analysis (VEDA) techniques and odour classification methods as well as other key properties.



**Figure 6.1:** Flavour wheel used by brewers to illustrate and communicate the International Flavour Terminology System for beer. This comprises 14 classes, 44 first-tier terms and 78 second-tier terms (not shown), (Reprinted from ASBC, Methods of Analysis [1976]<sup>81</sup>).



**Figure 6.2:** The training of an electronic nose to provide organoleptically defined flavour descriptors. A number of sensory trials,  $n$ , are made by a flavour panel on a single analyte, to produce scores,  $(Y_1, Y_2, \dots, Y_k, \dots, Y_p)$  under a set of  $p$  flavour descriptors (such as might derive from a flavour terminology system). The same odour is presented to an array of  $R$  sensors ( $R = 3$ ) in this example to generate a response vector  $(V_1, V_2, \dots, V_k, \dots, V_R)$  and  $n$  samples are taken. The total set of sensory descriptors  $\mathbf{Y}$  are then used as training data for an associative memory or mapping network (such as MLP), using  $\mathbf{V}$  as its input data.

Priority		Requirement
Essential	1.	Partial specificity of sensor elements
	2.	Overlapping response of sensor elements
	3.	Fast, reproducible and reversible responses
Desirable	1.	Monotonic near-linear sensor response
	2.	Stable response characteristics
	3.	Good stereochemical sensitivity
Ideal	1.	Small device size
	2.	Low power consumption
	3.	Ease of fabrication
	4.	Low noise

**Table 2.1:** A number of essential, desirable and ideal requirements of odour sensors for use in an electronic nose.

Array Type	Group - Country	No. Channels	Pre-processing		PARC	Applications	Refs.	
			Type	Norm.				
<b>Sintered metal oxide chemiresistors</b>	Warwick, UK	3				SO	7	
					LR,FW	SO,TO	10	
		12			LS	SO,CO	11,12	
			DFR	A	PCA,CA	SO,BV	13	
			LDFR	S	MLP	SO,BE	14,15	
	Walmsley et al.	3†	D		PCA,CA,LS	SO	16	
	Corcoran & Lowery	12	FR	S	MLP,KOH	WI	17	
	Hoffheins	6	RD	A	LS	SO	18,19	
	Carey et al.	8†				SO	20	
					MLP,LS	SO	21	
	Ikegami et al.	6		A	LS	SO	22,23	
	Abe et al.	7-8	LR	A	LR,PCA,CA	SO	24,25	
	Aishima	6	D	S	CL,PCA, DFA	SP,CO	26,27	
	Nakamoto et al.	3	D		MLP	SO	28	
	Egashira et al.	6				FI	29	
	Davide et al.	6			KOH	SO	30	
	Ólafsson et al.	3	D			FI	31	
Yea et al.	3	D		FUZ	SO	32		
<b>Organic polymers on chemiresistors</b>	Warwick, UK	12	F	A	LS,CA	BE	33	
		18-24	F	S	LS,MLP	BE	34,35	
	UMIST, UK	5				SO	36,37	
		20-32	D	A	PCA,BAY,MLP	CH,SO	38-41	
	Slater et al.	4	R	A	PCA	SP	42	
	Barker et al.	3	F		MLP	SO	43	
	on SAW devices	Ballantine et al.	12	R			44-46	
<b>Lipid layers on piezoelectric crystals</b>	Nakamoto & Moriizumi	8		A	MLP,PCA, FLVQ	SP,PE, SO	47-52	
		Muramatsu	4	D	S		SO	53
	Yokoyama et al.	8			PCA,CA	SO	54	
	Okahata et al.	6	D			SO	55,56	
	on SAW devices	Ohnishi et al.	6	D			PE	57
		Chang et al.	4	D	AS		SO	58
<b>MOSFETs</b>	Linköping, Sweden	10			MLP,KOH	ME	59	
		324	D			SO	60	
<b>Electrochemical Cells</b>	Stetter et al.	2-18		A	KNN	GR	61,62	
	Göpel et al.	8			PCA,PCR,LS	FI	63	

**Table 2.2:** Review of electronic nose systems classified by sensor array type. The main studies carried out in this area are shown under each research group, or individuals. For each system the following information is provided - The number of sensing channels used in the study (No. Channels), the type of pre-processing model used (Type) and whether normalisation of data was carried out (Norm.), the type of pattern recognition (PARC) technique used and which applications were studied. See Section 4 for a full description of pre-processing techniques. Pre-processing Type; Logarithm - L, Difference - D, Fractional - F, Relative - R. Pre-processing Normalisation; S - Sensor Normalisation, A - Array Normalisation. Pattern Recognition Techniques; Fuzzy Reasoning - FUZ, Discriminant Function Analysis - DFA, Linear Regression - LR, Least squares - LS, Principal Components Analysis - PCA, Cluster Analysis - CA, Multi-layer Perceptron - MLP, Fuzzy Learning Vector Quantisation - FLVQ, Kohonen Network - KOH, Feature Weighting - FW, Bayes Classifier - BAY, K-Nearest-Neighbour - KNN. Applications; Simple Odours - SO, Beverages - BV, Wines - WI, Beers - BE, Spirits - SP, Coffee - CO, Cheese - CH, Perfumes - PE, Meat - ME, Grains - GR, Fish - FI, Tobaccos - TO, († - Thin-film metal oxide semiconductor devices).

Property	Thick Film (SnO <sub>2</sub> )	Thin Film (SnO <sub>2</sub> )	Polymeric Chemiresistor	Olfactory Receptor
Fabrication	Manual	Sputtering Large Batch	Electrochemical Growth	Selective Expression gene pool - adaptive
Size	3 x 1mm	< 1 mm <sup>2</sup>	< 1 mm <sup>2</sup>	Sub-micron
Key measurand	Resistance	Resistance	Resistance	Spike Frequency
Integrated Array	No	Yes	Yes	Yes
Choice of Material	Limited	Limited	Wide	Wide
Operating Temperature	250-600°C	250-600°C	10-110°C	37°C
Power Consumption	≈ 800 mW	≈ 80 mW	< 10 mW	≈ nW
Molecular Receptive Range (MRR)	Combustible Vapours	Combustible Vapours	Wide Range	Volatile Organics
Response time	≈ 20 s	≈ 20 s	≈ 60 s	≈ 100 ms
Sensitivity	10-1000 ppm	1-100 ppm	> 20 ppm	1 ppm (down to sub-ppb)
Steric Sensitivity	None	None	Possible	High
Stability	Poor	Poor	Moderate	Disposable with continuous regeneration
Interferences	SO <sub>2</sub> , Cl <sub>2</sub> , water	Cl <sub>2</sub> , SO <sub>2</sub> water	Acidic gases, water	Infection, Reactive Vapours

**Table 2.3:** Comparison of the properties of different types of sensor element with those of the biological system, (Adapted from Dodd *et al.* [1992]<sup>66</sup>).

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