# Electronic Odour Measurement and Sensing using E-Nose

Vineeta Gupta , Komal Gupta

**Abstract**— An instrument for electronic odour sensing has been developed and used to classify many different materials, including beers, spirits and alcohols. The next stage in development is to begin to relate subjective odour descriptors (e.g. fruity, minty) to quantitative sensor array measurements. Both neural network and multivariate statistical techniques are required to accomplish this task . The ultimate goal is to provide a measurement standard for odours. The integration of sensor technology, signal conditioning, data acquisition and pattern recognition are required for this exciting prospect. An electronic nose (e-nose) is an intelligent sensing device that uses an array of gas sensors of partial and overlapping selectivity along with a pattern recognition component to distinguish between both simple and complex odors. To date in a number of applications from the food industry to medical diagnosis e- noses are used.

**Index Terms** — electronic odour , sensing device , electronic noses (e-nose) , odour measurement , machine olfaction .

## 1 INTRODUCTION

Recent technological advances have aroused interest in the possibility of mimicking, via electronic means, a mammalian nose. Such a device would have an enormous number of potential applications. However, there may be no advantage in attempting to copy the mammalian olfactory system. A typical instrument for simulating the function of the nose may be based upon the configuration shown in Fig. 3. This consists of a sensor array, with appropriate signal conditioning, connected to a pattern recognition system. Data, stored in memory, is used to classify calibrand colors and the results output to an instrument display. Successful system design will be a result of optimising the implementation of each system component. This paper provides an overview of the technology presently available for the design of such a system. The ability to artificially replicate the biological sense of smell has been a topic of interest to the sensor community for several decades. Devices called electronic noses or e-noses made their debut in the 1980's and using an array of gassensors togeth er with pattern recognition techniques, e-noses have been used to distinguish a variety of odors [23, 21, 22]. In more recent years, advances in electronics, sensors and computing have made the manufacturing of compact electronic nose devices possible, and particularly suitable for integration onto platforms such as mobile robots or intelligent appliances [20, 19, 18]. Currently works in the field of e-noses have mainly considered the devices on their own as singular stand alone odor analysists. Few exceptions exist where electronic noses have been combined with other chemical sensors such as electronic tongues for quality evaluation [24]. This is an important combination which attempts to bridge the gap between the human perceptual system and the electronic counterpart.

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## 2 DEFINING ODOUR

An odorant is a substance capable of eliciting an olfactory response whereas odor is the sensation resulting from stimulation of the olfactory organs. Odor threshold is a term used to identify the concentration at which animals respond 50 percent of the time to repeated presentations of an odorant being tested. Most often, however, odor "threshold" is used to describe the detection threshold, which identifi es the concen tra tion at which 50 percent of a human panel can identify the presence of an odor or odorant without characterizing the stimulus. Therecognition threshold is the concentration at which 50 percent of the panel can identify the odorant or odor.

Although the detection threshold concen trations of sub stanc es that evoke a smell are low, often times in the parts per billion (ppb) or parts per trillion (ppt) range, a concentration only 10 to 50 times above the detection threshold value often is the maximum intensity that can be detected by humans. This is in contrast to other sensory systems where maximum intensities are many more multiples of threshold intensi ties. For example, the maximum intensity of sight is about 500,000 times that of the threshold intensity and a factor of 1 trillion is observed for hearing. For this reason, smell is often concerned with identify ing the presence or absence of odor rather than with quantifying intensi ty or concentration.

Perception of a mixture of odorants, such as those in livestock odor, is very different from how each chemical would be perceived independently. Odorants can act as additive agents, counteractants, masking agents, or be synergistic in nature. The combination of two odorants can have an odor equal to that of either one of the components, have an odor less than that of one of the components, have an odor equal to the sum of the components, or even have an odor greater than the sum of the components. This makes odor quantifi cation and characterization a challenging process.

Odor can be evaluated subjectively in terms of intensity (strength) or in terms of quality (i.e., offensiveness). Odor quality

is evaluated by describing the odor or comparing the sample odor to familiar odors. Evaluation of odor quality is diffi cult because of the challenges that come with trying to describe odors.

## 3 ODOUR MEASUREMENT TECHNIQUES

### 3.1 Dilution-to-threshold methods

Dilution-to-threshold techniques dilute an odor sample with odorless air at a number of levels and the dilution series is presented in ascending order of odor concentration. From one level to the next, the dilution decreases and the amount of odorous air increases. The fi rst few levels include the sample diluted with a large amount of odorless air so evaluation can begin below the threshold of detection. Preferably, multiple presentations (two odorless air samples and the diluted odor sample) are made at each level of dilution. When a forced-choice method is used, a panelist, typically trained to conduct these evaluations, must identify the presentation that is different from the others at each level, even if it is a guess. This permits use of all the data. The threshold of detection is the dilution level at which the panelist can determine a difference between the diluted and the odorless samples. After the detection threshold is reached, the panelist continues the evaluation at the next level or two to be certain the identifi cation was not made by chance. Examples of the dilution-to-threshold methods include use of scentometery and olfactometery.

#### Scentometry

One method of odor concentration evaluation that is available on-site employs the use of a Scentometer (Barneby and Cheney, Columbus, OH) or a Nasal Ranger (St. Croix Sensor y, St. Elmo, MN). The Scentometer is a plastic box with a number of air inlets and two sniffi ng ports. Two of the air inlets have activated charcoal fi lters to remove odors and provide clean air. The remaining inlets are of varying diameter to permit a range of dilutions of odorous air to be sampled. An observer begins by opening the port of smallest diameter to start with the largest dilution (lowest concentration) of the odor.

As successively larger ports are opened, the dilution of the odorous air decreases and the odor concentration increases. When the evaluator can fi rst detect the odor, the odor threshold has been reached. Odor concentrations are expressed as dilutions to threshold. The range of dilutions to threshold possible for the Scentometer includes 1.5, 2, 7, 15, 31, 170, and 350. The Nasal Ranger operates on the same principles and has selectable dilution ratios of 2, 4, 7, 15, 30, and 60. Inhalation or airfl ow rate is controlled on the Nasal Ranger. For both instruments, an individual observer or a couple of people rather than a larger panel of evaluators frequently conducts measurements.

#### Olfactometry

Olfactometers operate much like the Scentometer and the Nasal Ranger. The primary differences are that olfactometers are not portable and an operator closely controls sample delivery. Larger dilutionto- threshold ranges are available. The AS'CENT International Olfactometer (St. Croix Sensory, St. Elmo, Minn.), for example, allows samples to be presented at 14 dilutions that represent a range in dilution-to-threshold of 8 to 66,667. These units are often used in a laboratory setting by 7 to 10 panelists to evaluate each sample rather than the small number of evaluators that are used in the fi eld measurements (See fig. 2). Efforts to establish the relationship between olfactometer readings and that from the portable units are currently underway at Iowa State University.

Fig. 1.Using a Nasal Ranger to detect odour

Fig. 2.Olfactometer

### 3.2 Ranking Methods

Odor can be evaluated using panelists to rank samples, a procedure in which an arbitrary scale is used to describe either the intensity or offensiveness of an odor. Typically, a scale of 0 to 10 is used, with 0 indicating no odor or not offensive and 10 representing a very intense or offensive odor. Such methods use either odor adsorbed onto cotton or a liquid sample that has been dilut-

ed. Manure can be diluted with water to a range of concentrations and then evaluated by a panel.

One study, for example, diluted stored dairy manure with water to create fi ve dilution levels. For each level, two blank samples of water and one diluted manure sample were presented in fl asks that had been painted black to avoid bias based on appearance ofthe diluted manure. Panelists evaluated the samples in an ascending series; the dilution decreased and odor increased from one level to the next. At each dilution level, panelists identifi ed the fl ask in each set of three that contains the odourus sample (Forced choice). A separate study analyzed panelist variability when this procdure was used and observed that each panel member had a distinct and repeatable odor probability distribution.

### 3.3 Referencing Methods

This method uses different amounts of 1-butanol as a standard to which sample odor intensity is compared, again using a human panel. The range of 1-butanol concentrations is often from 0 to 80 ppm. As the concentration of butanol is changed, the sample odor is compared to the butanol to determine at what concentration of butanol the sample's intensity is equivalent. The use of butanol as a reference standard is widely accepted as common practice in Europe and has been incorporated into portable and laboratory scale instrumentation. Most of the methods currently used in the United States employ butanol as a means of assessing panelist suitability rather than as the sole means of determining an odor's strength or acceptability.

## 4 SENSOR TECHNOLOGY

It is suggested here that the difference between odour sensing and gas sensing is that the former involves the description of a complex mixture of gaseous species, e.g. coffee aroma. Odour sensing can therefore be thought of as a relatively new application of gas sensors.There are many different types of sensor technology which can be used for odour classification. Of primary importance in any system design is the size of the sensor array. If many sensing elements are required, the optimum solution may involve the use of an integrated sensor array, rather than an array of discrete devices.The different types of available devices (resistors, capacitors,FETs) and materials (metal oxides,conducting polymers) offer many possible practical configurations. Formerly, gas sensors were designed to detect specific gases in atmospheres where certain concentrations of the gas may be hazardous[1]. Zaromb and Stetter were the first to propose the use of an array of sensors to analyse complex mixtures of gases[2 ].In practice, the detection mechanism of the sensors results in some inherent cross-sensitivity and the effectiveness of both gas and odour sensors can be described in terms of this cross-sensitivity. For gas detection, the sensor should show a high degree of specificity, whereas for odour detection the sensors would exhibit overlapping sensitivity to a wide range of materials. The three types of sensor most commonly applied in this field are described below.

### 4.1 The Taguchi gas sensor (TGS)

These commercially available metal oxide devices have been used by a number of groups for monitoring gases[2,3] and odours[4,5].Their basic construction is shown in Fig. 4a. The metal oxide, usually tin, can be doped with catalysts to produce a range of sensors with different sensitivity spectrums. The change in conductance of the tin oxide film between the electrodes is the output variable. McAleer etal[7] suggest a reaction mechanism in which, at elevated temperatures, adsorption of negatively charged oxygen species at the tin oxide surface takes place. The surface charge sets up a depletion layer and hence modulates the sensor conductivity. Reducing gases may be adsorbed, donating electrons or becoming positively charged surface species; alternatively, they may react with the surface oxygen species, releasing bound electrons.These space charge layers may also appear at the metalsemiconductor contacts and grain boundaries, where they can dominate the overall conductance[7] Taguchi gas sensors are very robust, but typically require around 1 watt of power for operation at 350°C. This high temperature is required for all metal oxide devices to facilitate the sensing mechanism (reaction, adsorption and desorption of atmospheric components at the sensor surface).

### 4.2 Integrated metal oxide sensors

Using thin-film metal oxide sensor fabrication techniques enables close control of the fabrication parameters and hence sensor performance. The gas-sensitive films are usually deposited using controlled reactive sputteringtechniques, which enhance sensol reproducibility from batch to batch. This approach has enhanced the development of microsensors, but requires careful consideration of the sensor encapsulation for operation at elevated temperatures. Th compatibility of thin-film processing with silicon processing has enhanced the development of integrated odour sensor[8,9] (Fig.4b). The metal oxide reaction at the surface of the sensor is identical to that of the thick-film TGS device but the effect can be different in that the sputtered layer may be dense and impermeable, limiting diffusion of the atmospheric components into the bulk of the material via grain boundaries.

### 4.3 Organic odour sensors

The majority of these devices are made using either conducting polymers or Langmuir-Blodgett (LB) films. Unlike metal oxide sensors, many organic devices can be operated at room temperature and hence require much lower power consumptions and their thermal design is straightforward. This enables integrated array design on either alumina substrates or silicon" (Fig. 4c). The odour sensitivity is due to the modulation of the conduction when physical adsorption of a gas upon the polymer takes place. Ideally this is a reversible reaction and the sensor selectivity can be controlled by the polymer counter-ion, which determines the sreochemistry (i.e. spatial arrangement) of the polymer and hence the adsorption site parameters.

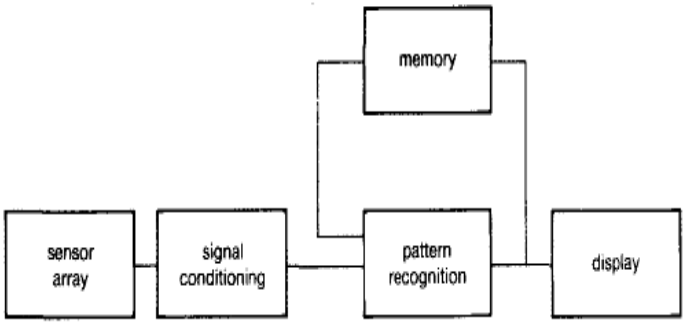



Fig. 3.Odour sensing system components

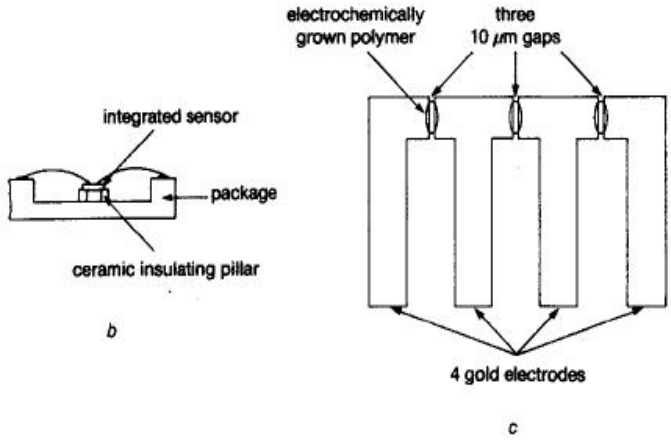
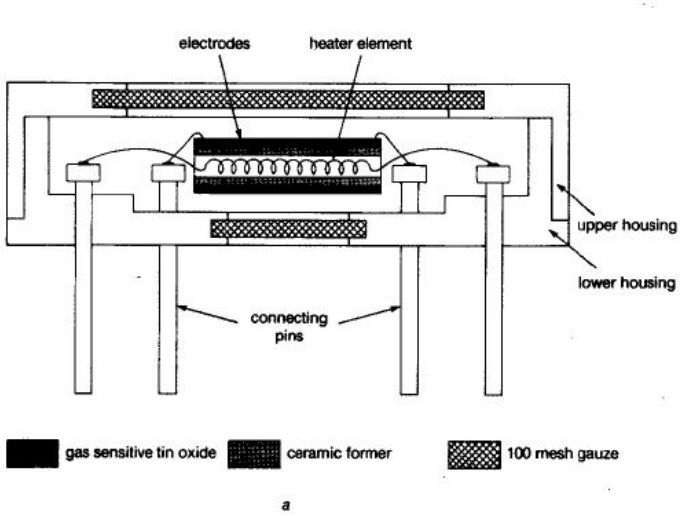



Fig. 4.Various types of gas and odour sensors (a)Taguchi gas sensor (b) integrated metal oxide sensor (c) conducting polymer sensor

## 5 SIGNAL CONDITIONING

To date, the majority of signalconditioning circuits used for interfacing have been very basic. Potential dividers, constant voltage sources or current supplies are common. Sophisticated instrumentation techniques have rarely been applied, and little attention has been given to the effects of quantisation and noise. However, if severe restrictions are not to be placed on system sensitivity and dynamic range, it is clear that the signal conditioning must be designed to ensure that the information provided by the sensor is maximised.[11]

AC measurement techniques (Fig. 5) can be used to optimise system sensitivity. These reduce the effects of noise by modulating the sensor signal at an audio frequency and then limiting the signal transmission bandwidth. Also, in utilising the bridge arrangement, the sensor output signal can be amplified to a suitable level, compatible with the dynamic range of the next stage. Using these techniques improves the apparent sensor detection limits of the TGS devices to the parts-per-billion range from the parts-per-million range.[12]




## 6 PATTERN RECOGNITION

The mammalian nose incorporates some very sophisticated pattern recognition features which combine extreme sensitivity with wide selectivity. It has been suggested that this is achieved by organising broadly tuned receptor cells in convergent neuron pathway[13] each of which transmits information related to a single feature of the odorous mixture. Hence simulation would imply that the electronic odoursensing system pattern recognition unit must contain some type of feature extraction.

Multivariate analysis, used to deal with measurements which have several variables of interest (i.e. sensor outputs), could be used to extract such features[14].T his technique attempts to extract information describing the simultaneous relationships between the variables. A widely used parametric technique is discriminant function analysis (DFA). This parametric technique uses assumptions about the data (i.e. multivariate normality, homoscedasticity) to help classify the data. In essence, DFA attempts to classify samples into known groups by constructing linear relationships for the predictor set of outputs (i.e. sensor outputs) and the criterion set of variables (i.e. odour classes). The relationships are constructed to aid the separation of odour classes. The functions are then further used to classify samples, producing statistically significant axes and assigning samples to the odour classes with calculated confidence levels. The functions are calculated such that the statistical F-ratio (mean value between groups divided by the mean value within groups) is maximised. Further discriminant functions are calculated, also maximising the Fratio, but subject to the condition that there is minimal correlation with previous functions.

Artificial Neural Network pattern recognition is also suitable for solving this type of problem[15,16]. These techniques provide a parallel distributed processing solution to odour identification. They can have several advantages over conventional techniques, including adaptability, noise and fault tolerance and fast operation once the network has been trained. However, a major disadvantage of Artificial neural network pattern the neural network whencompared to multivariate statistical techniques is the opaque

nature of the classifier. The statistical techniques can provide measures of confidence in the classification and additional information to help interpret which sensors are the most useful for discrimination (not necessarily the most sensitive elements). With a neural network, the knowledge is retained in the weights of the neuron interconnection matrix. Owing to the large number of interconnections necessary for even a very small network, it is difficult to extract information and measures of confidence describing the contribution of each sensor to the final classification.

A typical neural network may consist of three layers, trained using the back-propagation algorithm (Fig. 6). Here, the input layer would be excited by information from the sensor outputs, and this excitation would be passed, via the weights, through the second (hidden) layer, to the output layer. Therefore, the number of input neurons would be a function of the number of sensors used in the array, and the number of output neurons would typically be equal to the number of classes to be identified. The level of the signal from the neurons in the output layer, tor an unknown sample, would effectively classify the sample. During training, samples from the sensor array are presented to the input of the neura network, generating a network output vector which can be compared to a known target output vector. The error between the two can then be calculated and used as a guide to modifying the elements in the weights matrix, with subsequent iterations to further reduce the error. The iteration is made backwards through the network from the output layer to the input layer. If there is no difference between the target vector and the output vector the weights are not adjusted and no learning takes place. The detrimental effects of local minim2 on the error surface can be reduced by careful selection of learnin rates and momentum.

The application of pattern recognition algorithms to odour identification is still at an early stage. A sophisticated system may use several complementary techniques and intelligent processing to decipher the most relevant information provided by the sensors.

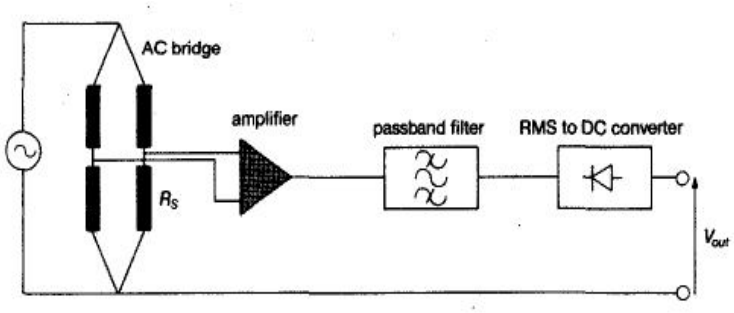



Fig. 5. A.C. measurement circuit schematic diagram

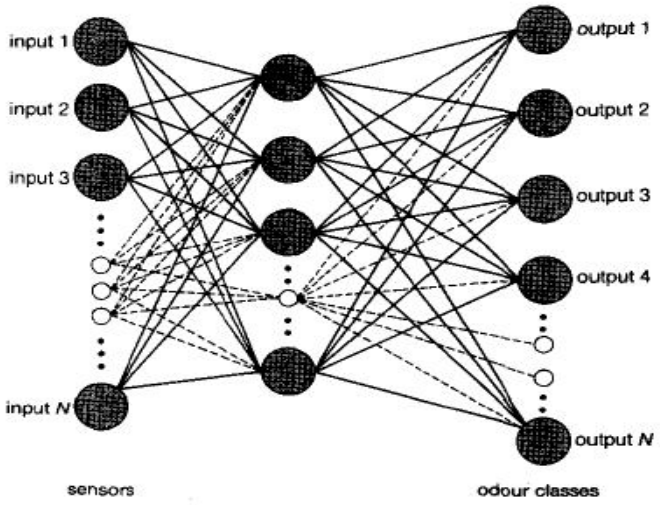



Fig. 6. Neural network structure for odour classification using the back – propogation algorithm

## 7 ELECTRONIC NOSE (E-NOSE)

The general accepted definition for an electronic nose is the following,
"An electronic nose is an instrument which comprises of an array of electronic chemical sensors with partial specificity and an appropriate pattern recognition system, capable of recognizing simple or complex odors." (Gardner, [5]).

The traditional architecture for the identification of odors is summarized in Fig 7. The basic principle is that each odor leaves a characteristic pattern or fingerprint of certain compounds. Based on this assumption, the process begins by collecting the signal responses from the each sensor, which occurs by converting the chemical reaction into an electrical signal. Many chemical sensors exhibit a response profile for several analytes. The degree of selectivity and the type of odors that can be detected largely depend on the choice and number of sensors in the sensor array.

The sensors are often mounted in an air tight chamber containing gas inlets and outlets to control the gas flow. The signals from each sensor are measuredand processed, usually by a analog to digital conversion that is performed by a computer. After the signal processing, the data is transformed by a variety of preprocessing techniques designed to reduce the complexity of the multi-sensor response. From this point, pattern recognition can be applied to differentiate substances from one another or train a system to provide a classification based on a collection of known responses.

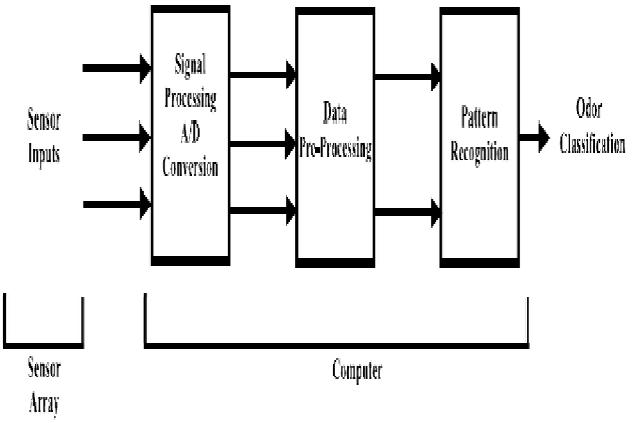



Fig. 7. An Odour Classification System

The term "electronic nose" is rather general and consequently can be misleading as far as its capabilities. In short, electronic noses are designed to mimic the human sense of smell by providing an analysis of individual chemicals or chemical mixtures. They offer an efficient way of analyzing and comparing odors. Electronic noses have yet to reach the capability of decomposing odors into their chemical components. Today, a variety of sensing technology is available ranging from metal oxide gas sensors to optical sensors. An equal if not larger variety of data processing techniques have been used with electronic nose data such as artificial neural networks (ANN), principal component analysis (PCA) and fuzzy based techniques. The possibility to quickly and effectively analyze odors has given rise to a number of industrial and research applications such as the monitoring and control of industrial processes, medical diagnosis, and control of food quality. odors. Electronic noses have yet to reach the capability of decomposing odors into their chemical components.

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Electronic nose analysis with a sensor array is a potential technology for odor evaluation. To date, relatively little research has been conducted with electronic noses in the area of agricultural manureodors. The electronic nose has been developed in an attempt to mimic the human sense of smell and is frequently used in the food, beverage, and perfume industries for product development and quality control.

The sensor array of an electronic nose detects the chemicals that humans perceive as odors and records numerical results. The instrument will generate a different pattern of response for different types of samples. Commercially available electronic noses have 32, 64, or 128 sensors. Each sensor has an individual characteristic response, and some of the sensors overlap and are sensitive to similar chemicals, as are the receptors in the human nose. A single sensor is partially responsive to a broad range of chemicals and more responsive to a narrow range of compounds. Multiple sensors in a single instrument provide for responsive to a great number and many types of chemicals, with certain sensors that mix being moderately to extremely sensitive to specific compounds.

The technology is relatively new to the agricultural industry, although the potential for application is certainly great. Recent work demonstrated that an electronic nose can distinguish between pig and chicken slurry and between emissions from swine and dairy facilities because the sensor response patterns between the comparisons were different. At the current point of development, the electronic nose appears to be less sensitive than olfactometry measures, though sensor improvements occur routinely. Sensor selection is critical from both the standpoint of sensitivity to compounds that contribute to the offensive odors (malodor) as well as response and durability of the sensors in humid environments.

## 8 ODOUR SENSING SYSTEMS

A simple system, based upon a static rig, is shown in Fig. 8. This system has been described elsewhere[5] The test procedure may vary somewhat depending on the measurand to be injected, but the essential steps for any test are as follows:
(a) The sensor head is placed in the flask, and is allowed to settle for a period of approximately one hour.
(b) The microcomputer-controlled sampling period is started and an appropriate quantity of measurand injected by syringe. As the measurand evaporates the sensors respond to the change in the atmospheric composition within the flask. The response of the sensor array is then recorded for the whole of the test sample period (typically around three minutes).
(c) The sensor head is removed from the flask and the air within the flask is blown out over a short period using a clean air supply.
(d) The sensor head is re-inserted into the flask and allowed to settle again before introduction of a further sample.

This process was undertaken to sample alcohols, beers, lagers and spirits. Analysis of this data using intelligent processing[5] principal component analysis (PCA) and cluster analysis (CLA)[14] and artificial neural networks (ANNs)[16] has shown considerable success. However, much of this work[14,16] used preprocessing algorithms incorporating sensor baseline drift measurements, and this was not suitable given the signalconditioning circuitry used. In the analysis described here disciminant function analysis (DFA) is applied to a data set of measurements representing the difference in sensor output resulting from exposure to a sample after some settling period in a reference atmosphere (i.e. clean air). In this case, it would be expected that DFA would perform better than PCA, since DFA constructs functions to help classify the data whereas PCA constructs functions to account for the variance of the data as a whole.

Twelve sensors were exposed to five alcohols (alcohol data set), and then two beers, two lagers and two spirits (beverage data set).

The sensor array showed a high degree of multicollinearity between its elements, and hence DFA would normally not be valid. However, DFA was still performed, but four randomly generated crossvalidation data sets were used todetermine whether the discriminant functions provided a reliable means of classifying the data. The results of applying DFA to the alcohol and beverage data sets is shown in Figs. 9a and b. The twelve normalised sensor outputs were reduced to two discriminant functions to produce points which were mapped on the twodimensional plots. The alcohols are clearly separable into five groups, a 100% correct classification rate. The scatterplots for the beverage data set enable separation between beers, lagers and spirits, but not between the two individual beers, the two lagers or the two spirits. Overall, the average classification rate for the four cross-validated data sets was 85%. To check whether the analysis of the four data sets arrived at similar solutions, irrespective of the random set used, the group centroids of the beverage data sets were analysed. From Fig. 10 it is clear that the analysis has arrived at similar functions for each cross-validated data set and the group centroids are much more closely related than the individual samples of data. For all six beverages there are clear boundaries between the group centroids of the classes. This implies that if the variation in sensor response to each class could be reduced, the classification rate would be much improved and more species could be identified using the same sensor array.

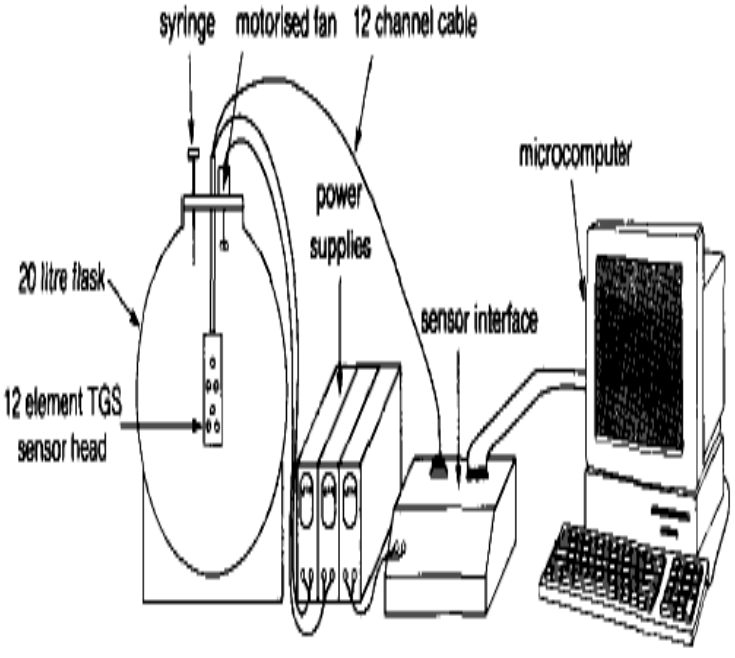
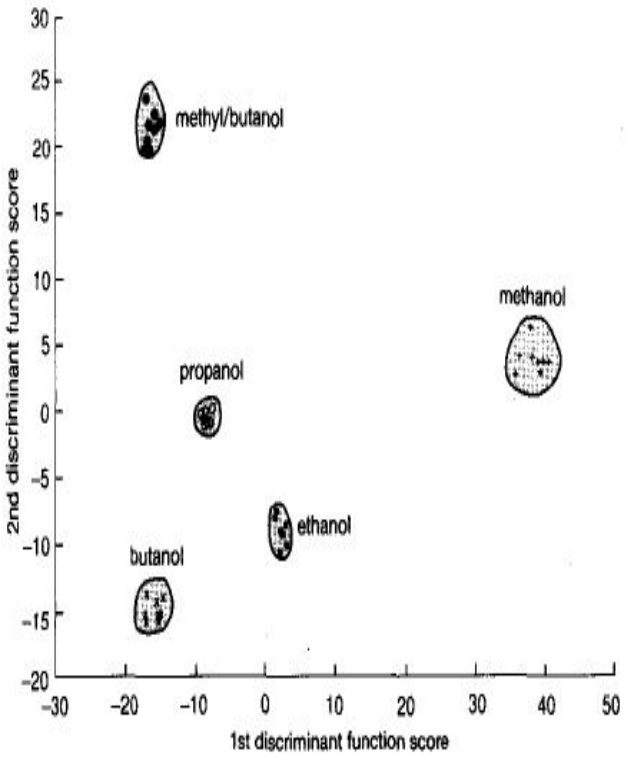
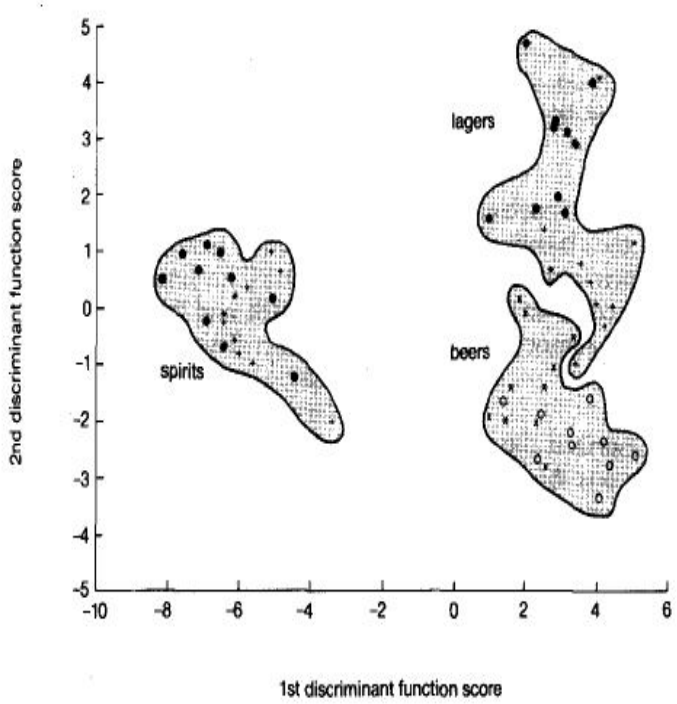



Fig. 8. Odour sensing system static rig




**Part : a**




**Part :b**

Fig. 9. Discriminant function analysis: (a) alcohol sample scatterplot using the first two discriminant functions - eight samples per class; (b) beverage sample scatterplot using the first two discriminant functions - ten samples per class

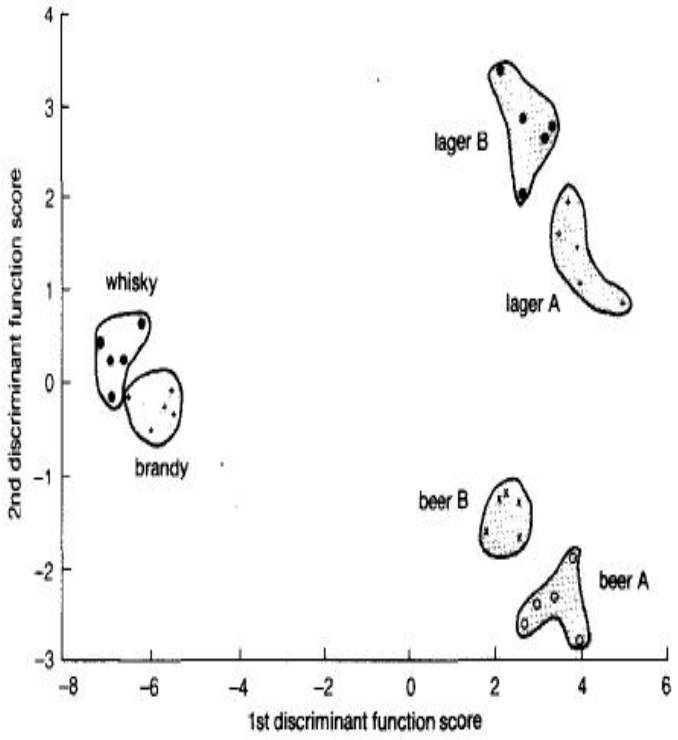



Fig. 10. Discriminant function analysis beverage group centroid scatterplot for four randomly generated data sets and complete data set

## 9 Challenges with current method

Challenges with current methodology include the use of humans for assessment. Work has shown that the same panelist's response from one day to the next can vary by as much as threefold, possibly due to health or mood of the individual. Variability in the sensitivity of the individual conducting the evaluation and odor fatigue are further concerns that are commonly addressed in procedural protocol.

Odor fatigue is a temporary condition where a person becomes acclimated to an odorant or odor to the point that they are no longer aware that the odor is present. An example would be when you walk into a barbeque restaurant and by the time you leave, you are unaware of the aroma that attracted you in the door. On-site methods are complicated by the infl uence that visual perception might have in an evaluation (smelling with your eyes, so to speak). Each of us has a unique odor acuity. While methods try to minimize panelist variation, the difference in sense of smell from one person is another consideration in human assessment methods.

The measurement of odor concentration by dilution is more direct and objective than that of odor quality or intensity. However, each of the above procedures requires the use of the human nose as a detector, so not one is completely objective. The imprecision that results from the large difference between the dilution levels has been identifi ed by researchers as a concern as well. Use of a forced-choice method, such as that used with dynamic olfactometers, in which a panelist must simply identify the presence or absence of an odor is generally a better method than ranking, as the human nose cannot distinguish small differences between levels of intensity.

## 10 Conclusion

Odor measurement is a complicated task. drawbacks. However, dilution-to-threshold methods are the Out of the number of methods available, none of the methods are without drawback.However dilution-to-threshold method is most widely accepted methods at the current time.The work described above shows that it is now possible to discriminate between complex odorous mixtures using well established techniques. At present, the scope of application is limited by the sensor technology. As more research directed towards gas and odour sensor devices , it may be possible to design selective sensors exhibiting reproducible responses to a comprehensive spectrum of odours in future. At this point in time, using techniques such as discriminant function analysis, it may then be possible to relate qualitative odour classes to quantitative measurements from a sensor array. This could be most easily achieved by mapping odour samples on a multidimensional scatterplot, which relates odour description (e.g. minty, fruity etc.) to specific regions on the plot. Such achievement would be of immense value in quality control of systems which presently rely on organoleptic profile panels.

## 11 Acknowledgment

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