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Modern Applications of Electronic Nose: A Review

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Article Info	ABSTRACT
	Electronic noses have provided a plethora of benefits to a variety of commercial industries, including the agricultural, biomedical, cosmetics, environmental, food, manufacturing, military, pharmaceutical, regulatory, and various scientific research fields. Advances have improved product attributes, uniformity, and consistency as a result of increases in quality control capabilities afforded by electronic-nose monitoring of all phases of industrial manufacturing processes. This paper is a review of some of the more important and modern applications that have been of greatest benefit to the humankind.

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1. FOODS AND DRINKS

1.1. Cooked Chicken Meat

Barbara Siegmund, Werner Pfannhauser(1999) had compared the results obtained by the new technique of the electronic nose to those gained by GC-MS and GC olfactometry (using comparative aroma extract dilution analysis).Chill storage at 4 7C of cooked chicken meat showed large increases in concentration as well as in flavour dilution factors of typical lipid oxidation products such as saturated and unsaturated aldehydes as well as alkylated furans, especially within the first 24 h. These results were confirmed by cluster analysis of selected lipid oxidation products. Analysing the chicken meat with an electronic nose showed results which are highly correlated with those obtained by commonly used and well known gas chromatographic techniques. They have demonstrated that the new analytical method of the electronic nose is a technique which can be used very well in flavour analysis as an additional rapid screening technique that does not require time-intensive sample pre-treatment [1].

1.2. Stored Oysters

Xiaopei Hu, Parameswara Kumar Mallikarjunan(2008) have studied the effectiveness of two electronic nose (e-nose) systems to assess the quality of on live oysters   stored at 4 and 7ºC for 14 days. E-nose data were correlated with a trained sensory panel evaluation by quantitative description analysis and with aerobic plate count. Oysters stored at both temperatures exhibited varying degrees of microbial spoilage, with bacterial load reaching 107 CFU/g at day 7 for 7ºC storage. Cyranose 320 e-nose system was capable of generating characterized smell prints to differentiate oyster qualities of varying age (100% separation). The validation results showed that Cyranose 320 can identify the quality of oysters in terms of storage time with 93% accuracy. Comparatively, the correct classification rate for VOC check e-nose was only 22%. Correlation of e-nose data with microbial counts suggested Cyranose 320 was able to predict the microbial

quality of oysters. Correlation of sensory panel scores with e-nose data revealed that e-nose has demonstrated potential as a quality assessment tool by mapping varying degrees of oyster quality.The developed methodology to evaluate the odor of oysters was able to produce a distinct smell-print of oysters stored at two temperatures for various time periods [2].

1.3. Processed Cheeses and Evaporated Milk

Laurent Pillonel et al (2001) investigated, processed cheeses and evaporated milk as reference materials, show that data transfer between two electronic noses based on mass spectrometry is possible and simple, the transfer of data between two SMartnoses does not require any complicated operations and is very user friendly. We showed that data imported from another instrument could easily be transferred to the training set of the original instrument and fit into the discrimination profile. They used evaporated milk and air as references for standardisation. Except for Glarissa, which shows a poorer repeatability in the PCA, all other cheeses (1/4 Fett, Emmental, Salami) and evaporated milk can be used as reference materials for standardisation [3].

1.4. Stored Vegetable Oils

N. Shen et al (2001) designed a project to determine the correlation between sensory evaluation and "electronic nose" analyses. Canola, corn, and soybean oils were stored at 60°C in the dark until sufficiently oxidized. On days 0, 3, 6, 9, and 12, oils were evaluated for peroxide value, for volatile compounds by "electronic nose," and for off-flavor by sensory evaluation. The results suggest that the "electronic nose" is capable of measuring changes in volatile compounds associated with oil oxidation and could be used to supplement data obtained from sensory evaluations [4].

1.5. Chocolates And Packaging Materials

Hans-Dieter Werlein (2001) were carried out Aroma analyses with the AromaScan using the multisampler technique and an array of 32 different polymer sensors. Optimum measurement parameters for the olfactory analysis of different kinds of chocolate and packaging materials printed with odorless and total odorless colors were developed. The discrimination of milk and plain chocolate was carried out at a temperature of 60^0C.The same temperature was needed for the discrimination of the four different milk chocolates. The fingerprints of the four milk chocolates were identical but they differed in intensity. The optimum temperature for the discrimination of the packaging materials was 120^0C. The transmission of volatile compounds from the packaging materials into the chocolate is also a subject of this article and can be established at a temperature of 120^0C. A clear discrimination between the chocolates stored with odorless and total odorless colored packaging material is possible [5].

1.6. Trimethylamine (TMA) in Milk

Silvia Ampuero et al (2002) have developed a simple, rapid, reliable and highly automated analytical method to determine trimethylamine (TMA) in milk using an MS based electronic nose (SMart Nose). A set of Swedish milk samples with and without naturally occurring TMA was used to compare this new method with sensory analysis and dynamic headspace (DHS) gas chromatography with flame ionisation detection (GC-FID). This analytical method developed within this investigation has been proved to be robust, reliable, and reproducible as it gives comparable results in runs performed at intervals of several weeks and with different MS emission filaments. As a result and because of the automatic sampling of the SMart Nose system, the present set-up can be programmed, without further optimisation, for non-stop analysis at a rate of a few min per sample. Therefore, this is an up to date method of choice for the quantitative determination of TMA in milk. It also provides further qualitative information on the milk analysed, such as the presence of additional off-flavours, using the full MS range and the PCA analysis supplied with this equipment [6].

1.7. Classification of Edible Oils

Z. Ali et al (2003) have developed an electronic nose utilising an array of six-bulk acoustic wave polymer coated Piezoelectric Quartz (PZQ) sensors. The nose was presented with 346 samples of fresh edible oil headspace volatiles, generated at 45°C. Extra virgin olives (EVO), Non-virgin olive oil (OI) and Sunflower oil (SFO), were used over a period of 30 days. The sensor responses were then analysed producing anarchitecture for the Radial Basis Function Artificial Neural Network (RBF). It was found that the RBF results were excellent, giving classifications of above 99% for the vegetable oil test samples [7].

1.8. Contaminated and Uncontaminated Milk

Z. Ali et al (2003) have successfully appliedheadspace analysis by means of sensor arrays to a wide range of qualitative applications. In this study, a six element array of coated Quartz Crystal Microbalance

(QCM) sensors was used for the headspace analysis of milk volatiles. The sensors were exposed to uncontaminated samples of milk and samples contaminated with Pseudomonas fragi(Ps. fragi) or Escherichia coli (E. coli). Principal component analysis (PCA) was used to analyse the sensor array responses. No discrimination between uncontaminated milk samples and those contaminated with Ps. fragiwas observed. This can be explained by Ps. fragibeing a poor fermenter of milk. However, encouraging results were found for the discrimination between the milk samples and those contaminated with E. coli [8].

1.9. Authenticity of the Botanical Origin of Honey

S. Ampuero et al (2003) have applied an electronic nose based on mass spectrometry to the control of the authenticity of the botanical origin of honey. PCA and DFA models were built based on groups of samples identified as typical unifloral honey by a classical method, i.e. a combination of sensory, pollen and physicochemical analysis. Swiss unifloral honeys of the following types were analysed: acacia, chestnut, dandelion, lime, fir and rape. Three different sampling modes were tested: static headspace (SHS), solid-phase micro-extraction (SPME) and inside needle dynamic extraction (INDEX). The last two showed interesting abilities to extract volatile components in a higher concentration and, most important, heavier compounds than SHS. The best classification, under the sampling conditions used, was provided by the SPME sampling mode. This method proved to be fast, reliable and powerful for this type of task. A good correlation was found between the present approach and the classical one for the determination of the botanical origin of honey [9].

1.10. Fruit Maturity

JesúsBrezmes et al (2005) have done a study to see whether an artificial olfactory system can be used as a nondestructive instrument to measure fruit maturity. In order to make an objective comparison, samples measured with our electronic nose prototype were later characterized using fruit quality techniques. The cultivars chosen for the study were peaches, nectarines, apples, and pears. With peaches and nectarines, a PCA analysis on the electronic nose measurements helped to guess optimal harvest dates that were in good agreement with the ones obtained with fruit quality techniques. A good correlation between sensor signals and some fruit quality indicators was also found. With pears, the study addressed the possibility of classifying samples regarding their ripeness state after different cold storage and shelf-life periods. A PCA analysis showed good separation between samples measured after a shelf-life period of seven days and samples with four or less days. Finally, the electronic nose monitored the shelf-life ripening of apples. A good correlation between electronic nose signals and firmness, starch index, and acidity parameters was found. These results prove that electronic noses have the potential of becoming a reliable instrument to assess fruit ripeness [10].

1.11. Mycotoxins in Wheat

G. Tognon et al (2005) develop the innovative method of the sensorial analysis (based on the use of an "electronic nose"), with the aim of evaluating its potential use as a rapid diagnostic test for determination of the levels of mycotoxin contamination in durum wheat[11]. The on-line evaluation of the quality of durum wheat (*Triticum durum*) represents, in terms of health and safety, one of the leading challenges of the milling industry.Knowledge of the content and distribution of mycotoxins on wheat kernel is very economically relevant and has great health implications due to its high impact on human health and on the safety of the use of decortication products in animal nutrition. The production of mycotoxins by particular mould strains is generally associated with the production of volatile substances such as alcohols, aldehydes, ketones and esters (Magan and Evans, 2000) [43].

1.12. Tea Quality Monitoring

S. Borah et al (2008) described an investigation into the performance of a Neural Network (NN) based Electronic Nose (EN) system, which can discriminate the aroma of different tea grades. The EN system comprising of an array of four tin-oxide gas sensors was used to sniff thirteen randomly selected tea grades, which were exemplars of eight categories in terms of aroma profiles. The mean and peak of the transient signals generated by the gas sensors, as a result of aroma sniffing, were treated as the feature vectors for the analysis. Principal Component Analysis (PCA) was used to visualise the different categories of aroma profiles. In addition, K-means and Kohonen's Self Organising Map (SOM) cluster analysis indicated there were eight clusters in the dataset. Data classification was performed using supervised NN classifiers; namely the Multi-Layer Perceptron (MLP) network, Radial Basis Function (RBF) network, and Constructive Probabilistic Neural Network (CPNN) were used for aroma classification. The results were that the three NNs performed as follows: 90.77, 92.31, and 93.85%, respectively in terms of classification accuracy. Hence the performance of the proposed method of aroma analysis demonstrates that it is possible to use NN based

EN to assist with the tea quality monitoring procedure during the tea grading process. In addition the results indicate the possibility for standardization of the tea aroma in numeric terms [12].

1.13. Classification of Black Tea

BipanTudu et al (2009) proposed, an incremental-learning fuzzy model for classification of black tea using electronic nose measurement, since commonly used classification algorithms are not capable of incremental learning. When a new pattern is presented to such a computational model, it can either classify the unknown pattern based on its legacy training or declare the pattern as an outlier if such a provision is built into the associated algorithm. In the case of the pattern being an outlier to the existing training model, it is desirable that the same could be seamlessly included in the training model with appropriate class labels so that a universal computational model may be evolved incrementally. To this end, classifiers having the incremental-learning ability can be of great benefit by automatically including the newly presented patterns in the training data set without affecting class integrity of the previously trained system. For application in black tea grade discrimination, an attempt has been made to correlate the multisensor aroma pattern of electronic nose with sensory panel (tea tasters) evaluation. However, this problem is associated with 2-D complexities. On one hand, the aroma of tea depends on the agro climatic condition of a particular location, the specific season of flush, and the colonial variation for the tea plant. On the other hand, the sensory evaluation is completely human dependent that often suffers from subjectivity and non repeatability. In our pursuit of developing a universal computational model capable of objectively assigning tea-taster-like scores to tea samples under test, it has been felt that an incremental approach could be extremely beneficial for electronic-nose-based tea quality estimation. To this end, the proposed incremental-learning fuzzy model promises to be a versatile pattern classification algorithm for black tea grade discrimination using electronic nose. The algorithm has been tested in some tea gardens of northeast India, and encouraging results have been obtained [13].

1.14. Adulteration of Virgin Coconut Oil

A. M. Marina et al (2009) have applied an electronic nose (zNoseTM) to the detection of adulteration of virgin coconut oil. The system, which is based on a surface acoustic wave sensor, was used to generate a pattern of volatile compounds present in the samples Principal component analysis (PCA) was used to differentiate between pure and adulterated samples. The PCA provided good differentiation of samples with 74% of the variation accounted for by PC 1 and 17% accounted for by PC 2. Pure samples formed a separate cluster from all of the adulterated samples [14].

1.15. Detection of Aflatoxins in Corn

A. Campagnoli et al(2009) analyzed five ground corn meal samples by a commercial direct competitive enzyme-linked immunosorbent assay (ELISA) for the determination of total aflatoxins, the results from electronic nose analysis clearly indicate that it was possible to differentiate between samples that had been contaminated and those that were not contaminated with aflatoxins[15]. These results were evident both in the case of naturally contaminated ground corn meal and in solutions fortified with synthetic aflatoxins. The results allowed us to assume that in the case of aflatoxins, the electronic nose was able to detect contamination by both the direct detection of toxins [45] and indirect recognition based on detection of volatile fungi metabolites associated to aflatoxins [46]. Aflatoxins are a group of toxic compounds produced by the secondary metabolism of toxigenic fungi, mainly of the Aspergillus genus. The occurrence of these toxins is frequent in food commodities, including cereals for human and animal consumption. Because of the highly heterogeneous distribution of aflatoxins in contaminated alimentary matrices, the availability of rapid and cost-effective analytical methods, which enable high sample throughput from the same lot, is urgently needed. From this point of view, the electronic nose appears to be a promising technology characterized by the required features. Previous experience has demonstrated that the electronic nose was able to distinguish between aflatoxins in natural contaminated corn samples according to the presence and absence of toxins[44].

1.16. Quality of Peaches

Hongmei Zhang et al (2009) used sensor array to establish a quality index model able to describe the different picking date of peaches. The principal component regression (PCR) and partial least-squares regressions (PLS) model represent very good ability in describing the quality indices of the selected three sets of peaches in calibration and prediction. The results showed that the PLS model represents a good ability in predicting quality index, with high correlation coefficients (R=0.86 for penetrating force [CF]; R=0.83 for sugar content [SC]; R=0.83 for pH) and relatively low standard error of prediction (SEP; 8.77 N, 0.299 °Brix, and 0.2 for CF, SC, and pH, respectively). The PCR model had high correlation coefficients (R=0.84, 0.82,

0.78 for CF, SC, and pH, respectively) between predicted and measured values and a relatively low SEP (7.33 N, 0.44 °Brix, 0.21 for CF, SC, and pH, respectively) for prediction. These results prove that the electronic noses have the potential to assess fruit quality indices [16].

1.17. Grape Products

Francisco Javier Cabañes et al (2009) used an electronic nose (e-nose) system using an array of metal oxide sensors (Fox 3000, Alpha MOS) to detect and discriminate two ochratoxigenic fungal species, Aspergilluscarbonarius (Bain.) Thom and A. Niger Van Tieghem, that are responsible for the contamination of wine and other wine grape products, using their volatile production patterns. Two well-known ochratoxigenic strains were used in this study: A. carbonarius A941 and A. Niger A75. These strains were grown on three culture media, CzapekDox modified (CDm) agar, yeast extract sucrose (YES) agar and white grape juice (WGJ) agar, and the volatile organic compounds produced in the headspace by these species were evaluated over periods of 48–120 h. The e-nose system was able to differentiate between the two species within 48 h of growth on YES and WGJ agar using principal component analysis (PCA), which accounted for 99.9% and 97.2% of the data respectively, in principal components 1 and 2, based on the qualitative volatile profiles. This differentiation was confirmed by cluster analysis of data. However, it was not possible to separate these species on CDm agar. Our results show that the two closely related ochratoxigenic species responsible for the contamination of wine and other wine grape products can be discriminated by the use of qualitative volatile fingerprints. This approach could have potential for rapid identification of A. carbonarius and A. Niger on wine grape samples, thereby significantly reducing the time of detection of these ochratoxinA producing species [42].

1.18. Rapid Halal Authentication

M. Nurjuliana et al (2010) used the electronic nose as a new potential rapid technique to analyze the aroma of various animals' body fats. The aroma fingerprints of four different animal fats and lard containing chicken fat were sufficiently specific to differentiate these fats based on their aroma composition. With principal component analysis (PCA), pure lard, pure chicken fats, beef fats, mutton fats, and adulterated samples were discriminated from each other. This work clearly shows the potential of the electronic nose as a rapid aroma profiling technique. Future works on the optimization of the experimental conditions need to be carried out. This study also demonstrated that the method developed has the potential for practical implementation in Halal authentication [17].

1.19. Palm Oil Identification

Eun Jeung Hong (2011) used an electronic nose based on mass spectrometer (MS-electronic nose) and GC to discriminate mixing ratios for mixtures of palm olein oil and palm stearin oil. The intensities of each fragment from the palm olein oil and palm stearin oil by the MS-electronic nose were used for discriminant function analysis (DFA). When palm olein oil is mixed with palm stearin oil, more than 3% of stearin oil can be estimated by DFA. The obtained data were used for DFA. DFA plot indicated a significant separation of pure palm olein oil and palm stearin oil. The added concentration of palm stearin oil to palm olein oil was highly correlated with the first discriminant function score (DF1). When palm stearin oil was added to palm olein oil, it was possible to predict the following equation; DF1= −0.112× (conc. of palm stearin oil)+0.416 (r2=0.95). When palm stearin oil was added to palm olein oil, peak area of GC was correlated to DF1 by MS-electronic nose with ratio of palm olein oil vs palm stearin oil. The MSelectronic nose system could be used as an efficient method for the authentication of oil [18].

1.20. Recognition of Coffee Quality

Kazimierz Brudzewski et al (2011) studied the application of the differential electronic nose for the recognition of coffee, particularly the forgery of it, made by mixing two different quality coffee brands (themediocre product and the high-quality coffee type), sold as the high-quality coffee brand. Since the beans are practically unrecognizable by the shape and visual inspection, the only solution to this problem is the application of the chemical analysis. The usually applied approach is the liquid chromatography. However, it is a laborious and expensive method, requiring special equipment and an experienced operator. In this paper, they propose the application of the differential electronic nose, relying its decision on the measurement of the coffee smell by the semiconductor gas sensors organized in the form of a matrix. They showed that differential electronic nose applying the special procedure of signal processing is of sufficient sensitivity for the recognition of the forgery of coffee and performs much better than the classical electronic nose (e-nose) [19].

1.21. Apple Storage

HuiGuohua et al (2012) investigated an electronic nose-based Fuji apple storage time prediction method. A home-made electronic nose with eight metal oxide semiconductors gas sensor array was used to measure the apples stored at room temperature. Principal component analysis cannot discriminate all samples. Stochastic resonance signal-to-noise ratio spectrum distinguishes fresh, medium, and aged apples successfully. The prediction model is developed based on signalto- noise ratio maximums. In validating experiments, results show that the predicting accuracy of this model is 84.62 %. This method takes some advantages including fast detection, easy operation, high accuracy, and good repeatability [20].

2. MEDICAL

2.1. Eye Bacteria Classification

RitabanDutta et al (2002) investigated an innovative data clustering approach for six bacteria data by combining the 3-dimensional scatter plot, FCM and SOM network. The combined use of three nonlinear methods (3D-Scatter plot, SOM, FCM) can solve the feature extraction problem with very complex data and enhance the performance of Cyranose 320. Later on two supervised ANN classifiers, PNN and RBF, were able to predict the six different bacteria classes with 94% and 98% accuracy respectively; where the training of the supervised ANN classifiers were performed using 40% of the whole data set for the six bacteria. Linear PCA method was able to classify four classes of bacteria out of six classes though in reality other two classes were not better evident from PCA analysis and we got 74% classification accuracy from PCA. An innovative data clustering approach was investigated for these bacteria data by combining the 3-dimensional scatter plot, FCM and SOM network. Using three data clustering algorithms (3-dimensional scatter plot, FCM and SOM network) simultaneously better 'classification' of six eye bacteria classes was represented. A [6×1] SOM network gave 96% accuracy for bacteria classification which was best accuracy. Then three supervised classifiers, namely Multi Layer Perce ptron (MLP), Probabilistic Neural network (PNN) and Radial basis function network (RBF), were used to classify the six bacteria classes [21].

2.2. Air-Conditioning Capacity of the Human Nose

Sara Naftali et al (2005) developed transient simulations in 3D models of the nasal cavity to study transport patterns in the human nose and its overall capacity to condition the inspired ambient air into alveolar conditions. The nose is the front line defender of the respiratory system. Unsteady simulations in three-dimensional models have been developed to study transport patterns in the human nose and its overall air-conditioning capacity. The results suggested that the healthy nose can efficiently provide about 90% of the heat and the water fluxes required to condition the ambient inspired air to near alveolar conditions in a variety of environmental conditions and independent of variations in internal structural components. The anatomical replica of the human nose showed the best performance and was able to provide 92% of the heating and 96% of the moisture needed to condition the inspired air to alveolar conditions. A detailed analysis explored the relative contribution of endonasal structural components to the air-conditioning process. During a moderate breathing effort, about 11% reduction in the efficacy of nasal air-conditioning capacity was observed [22].

2.3. Detection of Microbial Contaminations

Karl Kreij, Carl-Fredrik Mandenius (2005) used an electronic nose (EN) device to detect microbial and viral contaminations in a variety of animal cell culture systems. The emission of volatile components from the cultures accumulated in the bioreactor headspace was sampled and subsequently analysed by the EN device. The EN, which was equipped with an array of 17 chemical gas sensors of varying selectivity towards the sampled volatile molecules, generated response patterns of up to 85 computed signals. Each 15 or 20 min a new gas sample was taken generating a new response pattern. A software evaluation tool visualised the data mainly by using principal component analysis. The EN was first used to detect microbial contaminations in a Chinese hamster ovary (CHO) cell line producing a recombinant human macrophage colony stimulating factor (rhM-CSF). The CHO cell culture was contaminated by Escherichia coli, Pseudomonas aeruginosa, Staphylococcus aureus and Candida utilis which all were detected. The response patterns from the CHO cell culture were compared with monoculture references of the microorganisms. Second, contaminations were studied in an Sf-9 insect cell culture producing another recombinant protein (VP2 protein). Contaminants were detected from E. coli, a filamentous fungus and a baculovirus. Third, contamination of a human cell line, HEK-293, infected with E. coli exhibited comparable results. Fourth, bacterial contaminations could also be detected in cultures of a MLV vector producer cell line. Based on the overall experiences in this study it is concluded that the EN method has in a number of cases the potential to be developed into a useful on-line contamination alarm in order to support safety and economical operation for industrial cultivation [23].

2.4. Smelling Renal Dysfunction

Andreas Voss, VicoBaier (2005) have discussed that the human body odor plays an important role in social communication in various situations, like the olfactory identification of partners and relatives as well as in parents–child interactions. In patients with renal dysfunction the compound of sweat and volatile gases is changed because of the limited ability for removing metabolic products from the blood. The regulation of electrolyte composition and acid–base balance are also altered so that the body odor of these patientsmaybe significantly influenced by these disorders. We show the ability of an electronic nose to detect changes in the human body odor in consequence of renal dysfunction by reducing multivariate sensor signals with principal component analysis to its first and second principal odor component (POC). All healthy subjects could clearly be distinguished from patients with renal failure using quadratic discriminator analysis, whereas a correct classification of 95.2% (98.4% using 1st– 3rd POC) of patients between end stage renal failure and chronic renal failure was found. This methodology of analyzing human body odor may also provide new approaches for investigating symptoms of renal failure and for diagnosing other diseases of internal or cutaneous origin [24].

2.5. Detection of Boar Tainted Carcasses

S Ampuero and G Bee (2006) have evaluated the potential of an electronic nose (SMart Nose 151, LDZ, Switzerland) with a mass spectrometer (quadripole) as a detector to classify boar tainted carcasses. Obtained results demonstrated the potential of the electronic nose to detect high and low levels of boar taint, independently of the taint-related compound, and therefore to sort-out boar tainted carcasses [25].

2.6. Diagnosis of Chronic Rhinosinusitis

E. Bruno et al (2008) discussed that in otorhinolaryngologist's experience the nasal out-breath of people affected by chronic nasal or paranasal infections may be characterized by peculiar odours. In a previous study we showed that an electronic nose (EN), examining nasal out breath was able to distinguish subjects affected by chronic rhinosinusitis from healthy subjects. The present study is aimed at analysing the intensity and the quality of the odorous components present in the air expired by patients affected by rhinosinusitis, using a new EN based on gas-chromatography and surface acoustic wave analysis. In the gas-chromatographic tracings of the pathologic subjects there were six peaks, which were not present in control group cases. These peaks correspond to odorous components, whose chemical composition ranges from C6 to C14. Peaks obtained were compared with other tracings revealed from specific bacterial and fungal cultures analyses and some analogies are appreciated [26].

2.7. Study of Aerosolized Viable Influenza H5N1 Virus in Ferrets

Richard S Tuttle et al (2010) discussed that the routes by which humans acquire influenza H5N1 infections have not been fully elucidated. Based on the known biology of influenza viruses, four modes of transmission are most likely in humans: aerosol transmission, ingestion of undercooked contaminated infected poultry, transmission by large droplets and self-inoculation of the nasal mucosa by contaminated hands. In preparation of a study to resolve whether H5N1 viruses are transmissible by aerosol in an animal model that is a surrogate for humans, an inhalation exposure system for studies of aerosolized H5N1 viruses in ferrets was designed, assembled, and validated. Particular attention was paid towards system safety, efficacy of dissemination, the viability of aerosolized virus, and sampling methodology. An aerosol generation and delivery system, referred to as a Nose-Only Bioaerosol Exposure System (NBIES), was assembled and function tested. The NBIES passed all safety tests, met expected engineering parameters, required relatively small quantities of material to obtain the desired aerosol concentrations of influenza virus, and delivered doses with high-efficacy. Ferrets withstood a mock exposure trial without signs of stress. The NBIES delivers doses of aerosolized influenza viruses with high efficacy, and uses less starting material than other similar designs. Influenza H5N1 and H3N2 viruses remain stable under the conditions used for aerosol generation and sample collection. The NBIES is qualified for studies of aerosolized H5N1 virus [27].

2.8. Breathe Analysis of Lung Cancer Patients

Vanessa H. Tran et al (2010) discussed the measurement of gaseous compounds in exhaled breath, such as volatile organic compounds (VOCs), may provide a noninvasive technique for assessing lung pathology, some of which are associated with lung cancer (LC). VOC analysis is laborious while electronic noses are emerging as rapid detectors of an array of gaseous markers recognizing a characteristic "smell-print". They conduct a pilot breath analysis using an electronic nose to test the hypothesis that there would be significant differences in the smell-print patterns between newly diagnosed LC patients and control subjects.The results show promise in that there were significant differences in the smell-print of subjects with lung cancer compared with control subjects. Further standardization of the technique will assist in improving

the sensitivity and specificity of the method, with potential to use the analysis in a number of diseases where characteristic signatures occur in the breath [28].

3. CHEMICAL PROCESSES

3.1. Monitoring of the Composting Process

TiinaRajama Ki et al (2005) examined the effect of aeration on the composting process using two aeration levels representing insufficient and optimal aeration for composting. An additional aim was to identify possible indicator gases in the volatile organic compound profiles of the composts by on-line FT-IR and gas chromatographic determinations. The results indicated that the electronic nose was able to distinguish between the two composter bins after 13 days of composting. Of the volatile metabolites that were identified, methyl ethyl ketone (MEK) proved to be a suitable indicator compound of anaerobicity as it was only produced in considerable quantities in the insufficiently aerated composter bin [29].

3.2. Classification of Resistance to Western Flower Thrips in Chrysanthemums

Robin C. Mckellar et al (2005) tested a metal oxide sensor-based electronic nose for its ability to discriminate among chrysanthemum cultivars with varying degrees of resistance to western flower thrips (WFT), based on volatile chemicals released from cut leaves. Cultivars that were susceptible, intermediate, or resistant to WFT [based on mean cultivar rank (MCR)] were used as standards, and were correctly classified (> 90%) by using discriminant function analysis. Several cultivars with unknown resistance were classified based on the standards, and were used as standards in a subsequent trial to classify other unknowns. The results of this study demonstrate some agreement between the WFT resistance categories as designated by the electronic nose and results of feeding bioassays (MCR), suggesting that this technique may serve as a useful screening tool for WFT resistance [30].

3.3. Monitoring of Biotechnological Processes

Alisa Rudnitskaya, AndreyLegin (2008) evaluated an electronic nose consisting of MOSFET and MOS gas sensors and NIR spectroscopy combined with multivariate calibration (PLS-regression) as a tool for anaerobic digestion monitoring. A bioreactor was fed with a mixture of cellulose, albumin and minerals and exposed to an overload of glucose. It was demonstrated that electronic nose could follow changes in methane and acetate concentrations while NIR could predict microbial biomass and total volatile fatty acids and acetate content. Electronic tongues and noses offer the possibility to perform recognition and classification and quantitative determination of components' concentrations simultaneously in multicomponent media. This feature makes multisensor systems a promising tool for the processes follow-up, when the content of some components can be measured quantitatively and, at the same time, the state of the process and its correspondence to the normal operation conditions can be assessed [31].

3.4. Plant Degradation Analysis

Peter A. Lieberzeit et al (2008) discussed that continuous surveillance of composting processes would enable a feedback loop to be obtained for both analysis and process control. For this purpose, they have designed e-noses based on a six-electrode quartz-crystal microbalance (QCM) array coated with affinity materials and molecularly imprinted polymers (MIP). They enable quantitative monitoring of volatile organic compounds (VOCs) emitted directly in a compost bin and are highly suitable tools for achieving on-line characterization of the degradation processes occurring. During grass and pine composting (duration 14 days and 40 days, respectively), they observed concentrations of up to 250 ppm of esters, 700 ppm of alcohols, 250 ppm of terpenes, and 90% relative humidity directly on-line with such a system and could validate the data off-line by GC-MS. The sensor also gave direct insight into the differences between the two composting batch types. Besides duration, during grass composting larger amounts of alcohols are emitted whereas relative amount of terpenes is twice as high for pine composting. Detailed correlation of the sensor and the GC-MS data allows approximate estimation of the sensitivity of the sensor materials towards analyte classes such as, e.g., aliphatic alcohols or terpenes [40].

3.5. HAM Production

Marco CamardoLeggieri et al (2010) evaluated the potential use of qualitative volatile patterns produced by Penicilliumnordicum to discriminate between ochratoxin A (OTA) producers and non-producer strains on a ham-based medium. Experiments were carried out on a 3% ham medium at two water activities (aw; 0.995, 0.95) inoculated with P. nordicum spores and incubated at 25°C for up to 14 days. Growing colonies were sampled after 1, 2, 3, 7 and 14 days, placed in 30-ml vials, sealed and the head space analysed using a hybrid sensor electronic nose device. The effect of environmental conditions on growth and OTA

production was evaluated based on the qualitative response. However, after 7 days, it was possible to discriminate between strains grown at 0.995 aw, and after 14 days, the OTA producer and non-producer strain and the controls could be discriminated at both aw levels. This study suggests that volatile patterns produced by P. nordicumstrains may differ and be used to predict the presence of toxigenic contaminants in ham. This approach could be utilised in ham production as part of a quality assurance system for preventing OTA contamination [38].

3.6. Bioreactors for Monitoring the Off-Gas Patterns

Pablo E. Rosi et al (2011) designed specially an electronic nose and coupled to an air-lift bioreactor in order to perform on-line monitoring of released vapors. The sensor array was placed at the top of the bioreactor sensing the headspace in equilibrium with the evolving liquor at any time without the need of aspiration and pumping of gases into a separated sensor chamber. The device was applied to follow the off-gas of a bioreactor with Acidithio bacillus thiooxidans grown on beds of elemental sulfur under aerobic conditions. Evolution was monitored by acid titration, pH and optical density measurements. The electronic nose was capable to differentiate each day of reactor evolution since inoculation within periods marked off culture medium replacements using multivariate data analysis. Excellent discrimination was obtained indicating the potentiality for on-line monitoring in non-perturbed bioreactors. The prospects for electronic nose/bioreactor merging are valuable for whatever the bacterial strain or consortium used in terms of scent markers to monitor biochemical processes. [32]

4. ENVIRONMENTAL & POLLUTION CONTROL

4.1. Water Developments and Limitations

P. Hogben et al(2004) discussed that laboratory and field-based continuous water monitoring showed that introduced pollutants such as 2-chlorophenol and geosmin could be detected by a sensor array, however the detection limits were significant higher than the odour threshold concentrations (OTC) for the respective compounds. The conditioning of the monitoring system in a temperature controlled environment for on-line headspace generation and transfer reduced the impact of environmental fluctuations on the sensor response profiles. At present, a sensor array based monitoring system could be applied to the intake protection of taste and odour causing compounds in water supplies with a minimum OTC of 10 ppm [33].

4.2. Monitoring of Air Quality in the International Space Station

E. Martinelli et al (2007) illustrated the performance of an electronic nose in ground and space based experiments. In ground experiments the instrument demonstrated its ability to capture the malfunctioning of biofilters for animal cages and bioreactors chemicals removal. Space experiments showed that the main functionalities of the instruments are preserved at microgravity conditions and eventually, that the electronic nose technology is sufficiently mature for space applications [34].

4.3. Determination of C1–C3 Aliphatic Nitrohydrocarbons in Air

A. V. Kalach et al(2008) studied the responses of a sensor system to model gas solutions containing aliphatic nitrohydrocarbons over a wide concentration range (0.005– 0.075 g/m3). The maximum permissible concentrations of nitrohydrocarbons in workplace air (~0.03 g/m3) fall in this range. The aim of this work was to develop a multisensory electronic nose-type system as a set of piezoresonance sensors for the separate determination of C1–C3 aliphatic nitrohydrocarbons in air [35].

4.4. Detection of Environmental Pollutants

Hyuntae Kim et al(2011) developed an integrated chemical sensor array system for detection and identification of environmental pollutants in diesel and gasoline exhaust fumes. The system consists of a low noise floor analog front-end (AFE) followed by a signal processing stage. In this paper, we present techniques to detect, digitize, denoise and classify a certain set of analytes. The proposed AFE reads out the output of eight conductometric sensors and eight amperometric electrochemical sensors and achieves 91 dB SNR at 23.4 mW quiescent power consumption for all channels. They demonstrate signal denoising using a discrete wavelet transform based technique. Appropriate features are extracted from sensor data, and pattern classification methods are used to identify the analytes. Several existing pattern classification algorithms are used for analyte detection and the comparative results are presented [36]**.**

4.5. Livestock Farm

Leilei Pan, Simon X. Yang (2007) successfully developed a portable electronic nose with 14 gas sensors, a humidity sensor and a temperature sensor especially for objective measurement of livestock farm

odours. Experiments were conducted in field downwind from 14 livestock and poultry farms. Experimental results demonstrate that "Odour Expert" is a useful tool in supporting livestock and poultry farm odour management, which greatly improves the efficiency of livestock farm odour management and thus benefit livestock industry. The electronic nose is capable of producing accurate output with greater consistency in odourmeasurement. It is easier and cheaper to operate than using olfactometry or human panel. Thus it has good commercial potentiall[37].

Leilei Pan and Simon X. Yang (2009) also developed an electronic nose (e-nose)-based network system for monitoring odors in and around livestock farms remotely. This network is built from compact e-noses that are tailored to measure odor compounds and environmental conditions such as temperature, wind speed, and humidity. The e-noses are placed at various applicable locations in and around the farm, and the collected odor data are transmitted via wireless network to a computer server, where the data processing algorithms process and analyze the data. The developed e-nose network system enables more effective odor management capabilities for more efficient operation of odor control practice by providing consistent, comprehensive, real-time data about the environment and odor profile in and around the livestock farms. Experimental and simulation results demonstrate the effectiveness of the developed system [39].

4.6. Detective Services

C. Hädrich et al (2009) discussed the use of tracker dogs is the main method of finding hidden bodies, and in their search the dogs use typical scent patterns. "Electronic noses" can also be used to find and compare such patterns. Highly sensitive scent detectors have been successfully applied, e.g. in the examination of foodstuffs, in environmental tests and in material research. This study examined whether electronic sensors can be used to find bodies under outdoor conditions. The carcasses of two coneys were buried in soil at different depths. Over a period of 4 weeks, regular measurements were taken from the buried carcasses and from the control material. In addition, a "fingerprint" of the scent patterns was taken, and gas chromatography–mass spectrometry analyses were performed. Our findings indicate that it may be possible and viable to construct an "electronic body-tracking dog" [41].

5. FUTUREDEVELOPMENTS

There are numerous potential applications of electronic noses from the product and process control to the environmental monitoring of pollutants and diagnosis of medical complaints. However, this requires the developments of application-specific electronic nose technology that is electronic noses that have been designed for a particular application. This usually involves the selection of the appropriate active material, sensor type and pattern recognition scheme. The work has led to several commercial instruments, one employing commercial tin oxide sensors (Fox 2000, Alpha MOS, France) and another employing conducting polymer sensors (NOSE, Neotronics Ltd, UK). Future developments in the use of hybrid microsensor arrays and the development of adaptive artificial neural networking techniques will lead to superior electronic noses.The major areas of research being carried out in this field are:

1. Improved sensitivity for use with water quality and sensitive microorganism detection applications.
2. Identification of microorganisms to the strain level in a number of matrices, including food.
3. Improvement in sensitivity of the E-Nose for lower levels of organisms or smaller samples.
4. Identification of infections such as tuberculosis in noninvasive specimens (sputum, breath).
5. Development of sensors suitable for electronic nose use, and evaluation of unexploited sensors.
6.

6. CONCLUSION

With a vast amount of literature now available to demonstrate the theoretical and practical feasibility of using electronic noses in many diverse applications, the trick now will be to go the extra distance to begin to fine-tune these technologies for many practical and specific applications. This will require cooperative efforts and informative exchanges between researchers and practitioners. Once these difficulties and logistics are resolved, electronic-nose devices should be capable of solving many problems and serving many of the future needs of the industries that have yet to be discovered.

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