

Classification of fresh edible oils using a coated piezoelectric sensor array based electronic nose with soft computing approach for pattern recognition

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ABSTRACT

An electronic nose based on an array of six bulk acoustic wave polymer coated piezoelectric quartz (PZQ) sensors with soft computing based pattern recognition was used for the classification of edible oils. The electronic nose was presented with 346 samples of fresh edible oil headspace volatiles, generated at 45 °C. Extra virgin olive (EVO), non-virgin olive oil (NVO) and sunflower oil (SFO) were used over a period of 30 days. The sensor responses were visualised by plotting the results from Principal Component Analysis (PCA). Classification of edible oils was carried out using fuzzy c-means as well as radial basis function (RBF) neural networks both from a raw data and data after having been pre-processed by fuzzy c-means. The fuzzy c-means results were poor (74%) due to the different cluster sizes. The result of RBF with fuzzy c-means pre-processing was 95% and 99% for raw data input. RBF networks with fuzzy c-means pre-processing provide the advantage of a simple architecture that are quicker to train.

Keywords: Electronic Nose, Radial basis function, Fuzzy c-means, Edible Oils, Piezoelectric Quartz

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Nomenclature:

Δ	Change of frequency in Hz
f_o	the fundamental frequency of a quartz crystal in MHz
Δr_s	the mass of material deposited or sorbed onto the crystal in g
A	the area coated in cm ²
z	column vector
Z	set of N readings of z
Re	the universal set
U	the fuzzy partition matrix
$\mu_{i,k}$	the degree of membership to the i,k th element in U
D_{ik}	the distance measure of the i,k th element
v	the cluster centre of a fuzzy partitioned data set
V	the vector of cluster prototypes in a fuzzy c-means partition
A_i	the covariance matrix
y	the output from the hidden layer of a radial basis function network
\bar{x}	the mean of x
x	the analyte dataset
σ	the standard deviation
σ^2	the spread parameter for a radial basis function
μ_i	the standard deviation of the i th set
u	the output weights for a radial basis function network

1. Introduction

The quality control of odours and volatile compounds is important in many sectors ranging from the chemical to the environmental (Ali *et al.* 1999). Gas-Chromatography coupled to Mass-Spectrometry (GC-MS) is the most established and applied technique for the analysis of volatiles of interest to these areas (Hiserodt *et al.* 1997). A drawback to the use of GC-MS is the expensive equipment and the technical skills required to obtain adequate results.

Significant work has been carried out with this in mind on inexpensive portable instruments for online factory floor measurements. An electronic nose is a device that consists of an array of partially selective sensors coupled to a pattern recognition system (Persaud and Dodd, 1982). A variety of sensor systems including acoustic wave, semiconductor, optical and electrochemical sensors and many pattern recognition techniques have been employed (Martin *et al.* 1999) (Paulsson *et al.* 1999) (Stella *et al.* 2000) (Scott *et al.* 2003) (Fang *et al.* 1999) (Gardner and Bartlett, 1999). The nose system is capable of on-line and at-line measurements if it has been first trained off-line. An electronic olfactometer was used by Miele and Marquis (Miele and Marquis, 2001) to discriminate fresh grape juices at-line. High correlation was found between the olfactometer and high speed gas chromatography analysis carried out on the same samples. Llobet (Llobet *et al.* 1999) described a fuzzy ARTMAP (Fuzzy adaptive Resonance Theory Mapping) neural network to work in conjunction with an electronic nose. This supervised pattern recognition method has been shown to be capable of on-line learning without losing the information of already learnt patterns.

The fuzzy c-means algorithm is one of, if not the most popular non-hierarchical clustering techniques, the method derives from fuzzy logic theory and is able to assign fuzzy

memberships of data points to clusters. This has an advantage over so called hard clustering techniques where there is overlap between clusters; an individual point will have membership assigned to each cluster to a fuzzy degree. Linusson (Linusson *et al.* 1998) used fuzzy clustering to discriminate between alcohols in combinatorial chemistry, Barko (Barko *et al.* 1999) used it with data from an electronic nose to discriminate between various organic compounds, it was found that similar compounds like alcohols could be discriminated successfully.

Radial basis neural networks were popularised by Broomhead and Lowe in the late 1980's (Broomhead and Lowe, 1988), they are quick to train and conceptually elegant. Evans and co-workers used a RBF network with data from an electronic nose to determine the quality of wheat (Evans *et al.* 2000). The nose used an array of 32 conducting polymer sensors; the output was then pre-processed before classification being made by the RBF network. The reported success rate was 92% correct on a simple judgement between good and bad quality.

The authors have previously described work on the use of a PZQ sensor based electronic nose for gas phase pre-concentration measurement (Ali *et al.* 2003). There is also a need for the classification of different edible oils for issues of quality control, adulteration and authentication.

2. Sensors

2.1 Piezoelectric Quartz Crystals

The sensors are made from α -Quartz, a crystallographic system that exhibits piezoelectricity. This effect is utilised using gold electrodes attached to the quartz and exerting an alternating current that results in the crystal oscillating with a fundamental frequency. The PZQs used were AT cut ($35^{\circ}15'$ inclination in the y-z plane) with 5mm diameter circular gold electrodes on both sides of an 8 mm quartz wafer, connected to a HC49/U holder. Any layer added to the crystal, which does not dampen the oscillation may be treated as added thickness, causing a change in frequency that relates to a change in mass. A diagram of a PZQ sensor can be seen in figure 1 and a diagram of the oscillator circuit for the PZQ sensors is shown in figure 2. PZQs act as sensors by the immobilisation of a chemical or biochemical layer on the device surface. The chemical or biochemical layer is used to abstract analyte from the sample stream to the device surface. The Sauerbrey equation (1) demonstrates that the change in device frequency is proportional to the mass of material sorbed (adsorption or absorption) by the coating layer on the crystal surface (Sauerbrey, 1959).

$$\Delta f = -2.3 \times 10^6 \cdot f_o^2 \cdot \frac{\Delta m_s}{A} \quad (1)$$

The wide range of coating materials that may be used offers this sensor technology a large degree of selectivity for a given application. Quantative measurements in the parts-per-billion (ppb) detection range are possible (Carey and Kowalski, 1986). The PZQ sensors can be used at room temperature.

3. Nose System

3.1 Outline of electronic nose

The electronic nose system reported here is based on an array of six PZQ sensors each with a fundamental frequency of 10 MHz. A block diagram of the nose system is shown in figure 3, figure 4 shows a photograph of the system with the main components labelled. Each sensor is driven by its own oscillator circuit; a multiplexer enables a particular sensor to be selected. A mixer compares the selected sensor frequency to a reference frequency provided by an uncoated PZQ. A frequency counter allows the frequency difference to be collected over any given period. A PC is connected to the system via a PC30AT interface card and controls the sampling process. A selector switch allows a frequency meter to be connected to any given PZQ for individual checking and monitoring of the sensors. The software for both the data collection and analysis was written in C/C++.

4. Experimental

4.1 Apparatus

A block diagram of the experimental apparatus is shown in figure 5. Dry nitrogen enters the system and is split between a reference and sample flows balanced by flow controllers. The sample flow is passed into a Dreschel bottle containing the sample, maintained at a constant temperature. A four-way PTFE valve enables the flow to the sensor array to be switched between the reference and the sample streams.

4.2 PZ Quartz Crystal Coating

The PZQ sensors were each coated with a commonly utilised gas chromatography stationary phase. The coatings were chosen to provide limited selectivity to a broad range of compounds and give a wide range of functional groups and polarities. The PZQ coatings

used were OV-1, Carbowax 20M, OV-17, Diethylene glycol succinate, Silar 10C and OV-210. Dilute solutions (0.1% w/w) of each coating were prepared in a volatile solvent, either chloroform (CHCl_3) or an 80:20 v/v mixture toluene:methanol. As the solutions were applied to both sides of the PZQ the frequencies were monitored to ensure that the same quantity of coating had been applied to the device surface. After coating the sensors were conditioned prior to use by passing nitrogen over their surface for six hours.

4.3 Sampling

A Dreschel bottle containing 10 mL of edible oil was kept at a constant temperature of 45 °C for 30 minutes to allow for dynamic headspace generation. During sampling the test oil was maintained at 45 °C to maintain the headspace generation. The reference and sample gas streams were both held at 17 mL min⁻¹. Sampling was performed over a 3-minute cycle, 1 minute for reference flow and 2 minutes for sample flow. After each sample run the sensor chamber was purged with reference nitrogen flow for 5 minutes prior to the start of the next sample cycle. A total of 346 oil samples were taken, consisting of 112 extra virgin olive oil (EVO), 126 non-virgin olive oil (NVO) and 108 sunflower oil (SFO) samples.

5. Analysis Techniques

5.1 Principal Component Analysis

PCA is a commonly used multivariate technique (Byun *et al.* 1997), (Callan, 1999), which acts in an unsupervised manner. PCA finds an alternative set of axes about which a data set may be represented. It indicates along which axis there is the most variation; axes are

orthogonal to one another. PCA is designed to provide the best possible view of variability in the independent variables of a multivariate data set. If the principal component scores are plotted they may reveal natural clustering in the data and outlier samples. Using this technique provides an insight into how effective the pattern recognition system will be at classifying the data.

5.2 Fuzzy c-means

Fuzzy c-means is a clustering method of data analysis based on the fuzzy membership of each data point to each of the clusters of data formed. Conceived in 1973 by Dunn (Dunn, 1973) and generalised by Bezdek (Bezdek, 1981), the family of algorithms is based on an iterative optimisation of a fuzzy objective function. Due to the efficacy, simplicity and computational efficiency these have become very popular techniques

5.2.1 Fuzzy clustering

The Fuzzy c-means algorithm uses fuzzy weighting with positive weights to determine the centres of the c cluster prototypes; c must be given. The weights are set to minimise a constrained functional. As a point approaches a prototype centre its weight increases to unity, but as the distance increases the weight decreases and tend to become more uniform. The fuzzy c-means algorithm allows each feature vector to belong to multiple clusters with varying fuzzy membership values. It should be noted that convergence to a fuzzy weight set that minimises the functional is not assured for the fuzzy clustering algorithm due to local minima and saddle points. To overcome this, the initial weights of the feature vectors are randomly chosen and the process repeated several times to obtain a mean solution

The aim of cluster analysis is to group all data vectors into sub-sets according to the similarities amongst them. A cluster is a group of objects that have more similarities among them than other clusters. Typically this similarity is defined as the distance between vectors based on the length from a data vector to some prototypical object of the cluster. The prototypes are not usually known beforehand, and are calculated by the clustering algorithm simultaneously with the partitioning of the data. Accordingly clustering techniques are among the unsupervised learning methods, as they do not use prior knowledge of class identification. The prototypes may be vectors of the same dimension as the data objects, but may also be defined as higher-level geometrical shapes. The dataset Z is partitioned into c fuzzy subsets. Objects on the boundaries between classes are not forced to fully belong to any one of the classes. They are however assigned a membership of 0 to 1 indicating the degree to which the data vector belongs to that cluster.

If each data vector consists of n measured variables grouped into an n -dimensional column vector $z = [z_{1k}, \dots, z_{nk}]^T$ (shown transposed), $z_k \in \mathbb{R}^n$. A set of N observations is denoted by $Z = [z_k | k = 1, 2, \dots, N]$ and may be represented as an n row by N column matrix:

$$Z = \begin{bmatrix} z_{11} & z_{12} & \dots & z_{1N} \\ z_{21} & z_{22} & \dots & z_{2N} \\ \vdots & \vdots & \vdots & \vdots \\ z_{n1} & z_{n2} & \dots & z_{nN} \end{bmatrix} \quad (2)$$

In typical pattern recognition terminology, the columns of Z are the patterns or objects; the rows are called the features or attributes and Z called the pattern matrix.

Clustering divides the dataset Z into c clusters. A c by n matrix $U = [\mu_{ij}]$ represents fuzzy partitions if the elements satisfy the following conditions:

The fuzzy membership for each object to each cluster lies in the range $[0, 1]$

$$\mu_{ij} \in [0, 1] \quad 1 \leq i \leq c, \quad 1 \leq j \leq n \quad (3)$$

The sum of fuzzy memberships to all clusters for each object is 1.

$$\sum_{i=1}^c \mu_{ij} = 1 \quad 1 \leq j \leq n \quad (4)$$

The sum of fuzzy memberships for all objects to each cluster must be greater than 0 and less than N .

$$0 < \sum_{j=1}^n \mu_{ij} < N \quad 1 \leq i \leq c \quad (5)$$

where: c is the number of fuzzy clusters, μ_{ij} denotes the degree of membership. The

(transposed) $z = [z_{1k} \dots z_{nk}]^T$ - th observation belongs to the $1 \leq i \leq c$ cluster.

The objective of the fuzzy c-means algorithm is to minimise the sum of the weighted squared distances between the data points, z_k and the cluster centres, v_i . The distances D_{ik}^2 are weighted with the membership values $\mu_{i,k}$. The objective function is then:

$$J(Z, U, V) = \sum_{i=1}^n \sum_{k=1}^c \mu_{ik}^m \|z_k - x_i\|^2 \quad (6)$$

where:

$U = [\mu_{ik}]$ is the fuzzy partition matrix

$V = [v_1, v_2, \dots, v_c]$ is a vector of cluster prototypes (centres).

$m \in [1, \infty)$ is a weighting exponent that determines the fuzziness of the resulting clusters, it is commonly chosen to be $m = 2$.

D_{ik}^2 may be determined by any appropriate norm, for example Euclidean norm distance.

$$D_{ik} = \|z_k - x_i\| = \sqrt{(x_{ik} - z_{ik})^2 + \dots + (x_{ik} - z_{ik})^2} \quad (7)$$

The minimisation of the c-means functional represents a non-linear optimisation problem that may be solved using the alternating optimisation algorithm also known as the fuzzy c-means algorithm.

The Euclidean distance results in point prototypes and develops spherical clusters. The Gustafson and Kessel algorithm (Gustafson and Kessel, 1979) replaces the Euclidean distance by a metric that is induced by a positive definite matrix. It therefore can detect ellipsoidal clouds of data vectors. The clusters are still assumed to be approximately the same size. For example the Mahalanobis distance takes account of the different elliptical cluster orientations as well as the correlations of the data points.

$$D_{ik} = \sqrt{\mathbf{z}_k - \mathbf{v}_i \mathbf{A}_i^{-1} \mathbf{z}_k - \mathbf{v}_i}^T \quad (8)$$

The covariance matrix, A_i , may be estimated by:

$$A_i = \frac{\sum_{k=1}^N (\mathbf{z}_k - \mathbf{v}_i)(\mathbf{z}_k - \mathbf{v}_i)^T}{n - 1} \quad (9)$$

For this data set the variations to the clustering algorithm that allow elliptical cluster shapes are not needed, the Euclidean distance was used in all calculations.

5.2.2 The Fuzzy c-means Algorithm

Given the dataset Z ; choose the number of clusters c , the weighting exponent m , the termination tolerance $\varepsilon > 0$ and initialise the partition matrix randomly.

Loop ($l = 1, 2 \dots$) (*Calculate for a maximum number of iterations*)

Compute the cluster centres

$$\mathbf{v}_i^l = \frac{\sum_{k=1}^N \frac{z_k}{\sum_{j=1}^c \dots}, \quad 1 \leq i \leq c \quad (10)$$

Compute the distances (Euclidean)

$$D_{ik} = \|\mathbf{z}_k - \mathbf{v}_i\| = \sqrt{(\mathbf{z}_k - \mathbf{v}_i)^T (\mathbf{z}_k - \mathbf{v}_i)} \quad 1 \leq i \leq c, \quad 1 \leq k \leq n \quad (11)$$

Update the partition matrix

If $D_{ik} > 0$ for $1 \leq i \leq n; 1 \leq k \leq V$

$$\mu_{ik} = \frac{1}{\sum_{j=1}^c \frac{1}{D_{jk}^{2/(n-1)}}} \quad (12)$$

else

$$\mu_{ik} = 1 \quad (\text{Distance is zero, so membership is 1})$$

until $\|U^l - U^{l-1}\| < \epsilon$ (partition matrix {Euclidean norm} alters by less than a tolerance)

The calculation continues until the partition matrix alters by less than a tolerance (Euclidean Norm) value or a maximum number of iterations has been reached. A variation of this is to use the change in cluster centres V .

5.3 Radial basis neural network

5.3.1 RBF Overview

Radial basis function neural networks consist of a three-layer system of interconnected nodes; each layer is connected to the next layer by a weighted output. The feature space is normalised $[0, 1]^n$ by the input layer and is filled with M overlapping radial based functions. The functions are continuous and reach a maximum value at the centre of the specific region covered, but assume a near zero value outside of it. There are several types of radial

functions, the most popular being the gaussian. One way of describing a RBF network is that each radial function is a fuzzy set membership function in the feature space. Any feature vector x , belongs to one or more of the response regions, it is fuzzified by each radial basis function to the appropriate membership of that region, these outputs are weighted and summed to determine the match level for each class. It is the summing of the weighted outputs from the hidden layer that perform the fuzzy rule mapping to produce a classification.

5.3.2 RBF architecture

The centre of each RBF is placed on a small cluster that represents a subclass; therefore M functions cover the feature space. The spread parameter (σ^2) may be adjusted so that it covers a larger area; adjacent RBF's usually overlap to some degree. The neurons represented by the M centres make the single hidden layer of an N - M - C feed forward artificial neural network. The output layer C contains summing neurons with weighted connections to the hidden layer M that must be trained in a similar way to a multi layer perceptron network.

5.3.3 RBF operation

The operation of a trained network consists of presenting an input vector x , the input layer normalises the vector to $[0,1]$. The hidden layer to produce a scaled response to the normalised vector processes this using the Gaussian equation (13). Any input vector close to one of the M neuron centres will produce an output y that is greater than any other. The vector $y = (y_1, \dots, y_M)$ that is output from the hidden layer is processed by each neuron of the output layer. The output layer consists of a number of summing neurons, the output from

each hidden neuron is scaled according to a weighting value, all scaled outputs are then summed. The output node with the highest activation is considered the winner.

$$\mu(x_i) = \exp\left[-\frac{(x_i - \bar{x}_i)^2}{2\sigma_i^2}\right] \text{ where } i = 1, 2, \dots, n \quad (13)$$

where \bar{x} is the mean of x , the analyte data set for that sensor and σ is the corresponding standard deviation.

5.3.4 RBF training

Finding the centres, spread and weights of the hidden nodes constitutes training of an RBF network, the simplest method is to set the function centres according to a clustering algorithm, the spread parameter of all hidden nodes are equal and are not altered, training consists of iteratively adjusting the output weights to achieve minimum error. However, for optimal performance of an RBF network the position of the centres and spread of the hidden nodes is critical. The full training algorithm for radial basis function networks of Looney (Looney, 1997) allows adjustment of the hidden neuron centres v , the spread parameter σ^2 and the output weights u .

6. Results and Discussion

The sensor array data for the edible oils was visualised using PCA. Pattern recognition was applied using fuzzy c-means as well as RBF networks reading raw data and fuzzy c-means pre-processed data.

6.1 Principal Component Analysis Results

Figure 6 shows the first two principal components in a PCA scores plot for the 346 oil samples. The data set consists of 112 EVO oil, 126 NVO and 108 SFO samples. The data classes are clearly visible as clusters. The non-virgin olive oil forms a tight cluster to the right of the plot with a centre of (0.12, 0), the sunflower forms a less tight cluster to its left, centre (0.03, 0), and there is a small degree of overlap between these two classes. The extra virgin olive oil data forms a loose cluster to the left of the plot, centre (-0.18, 0); there are several outliers to this cluster some of which are closer to the sunflower cluster centre than the extra virgin olive oil cluster centre.

6.2 Results using fuzzy c-means

The results of applying the fuzzy c-means algorithm with $m = 2$ to the full oil data set are shown in table 1. The SFO has a poor classification rate, this is not surprising as all of the clusters are assumed to be spherical and of the same size which is not true for this data set. Figure 7 shows the fuzzy c-means partitions for the edible oils mapped onto the first two principal components surface. The outlying points for the sunflower oil have been partitioned to have a higher membership value for NVO. Similarly the outliers for the EVO closer to SFO are prescribed a higher membership value for SFO.

Fuzzy c-means may not be the ideal classification technique for this data, it may however be used as a pre-processing device to dimensionally reduce, whilst simultaneously normalising the data. For the three classes shown here the output from the c-means algorithm will be three values for each data set.

6.3 Results using RBF networks

Two RBF networks were used to classify the edible oil data, the first was trained on 233 points selected at random from the full data set of the raw (un-processed) data. The trained network was tested on all 346 data points for direct comparison with the fuzzy c-means results. Table 2 shows the results of using an RBF network with an architecture of 6-6-3. Only one SFO sample has been misclassified as NVO and one NVO as SFO, there were no misclassifications of EVO.

The second RBF network used data pre-processed by the fuzzy c-means algorithm, the six dimensional data set was reduced down to a three-dimensional set. A RBF network using a 3-4-3 configuration was trained on 233 data sets. The results of testing the network on all 346 data sets is shown for direct comparison with the fuzzy c-means output (used as input to this network). Table 3 shows that 16 SFO samples were misclassified as NVO a significant improvement on the 79 misclassified samples from the c-means, this is due to the optimised supervised training that the neural network uses.

6.4 Comparison of Pattern recognition approaches

The fuzzy c-means algorithm was able to cluster the data points into three clusters, however since one constraint with this algorithm is that all clusters are spherical and of the same size there were errors in the classifications produced. The overlap between the SFO and the NVO, coupled to the size (variance) difference between these clusters resulted in many of the resulting misclassifications.

The RBF network processing the raw data in a 6-6-3 architecture was able to correctly classify all but one data point. The full training algorithm employed was able to minimise the network error by incrementally adjusting the network variables (function centres, function spread and output weightings).

Using the fuzzy c-means algorithm to pre-process the nose data from six to three dimensions allowed a RBF network of a relatively simple 3-4-3 architecture to classify the data with an overall accuracy of 95%. All of the misclassifications were SFO data being incorrectly grouped as NVO; this is an unfortunate consequence of using the Euclidean distance in the calculations. All clusters are assumed to be spherical and of approximately the same size, a possible solution to this may be the use of a Gaussian mixture decomposition algorithm.

7. Conclusions

The fuzzy c-means algorithm is not appropriate for data sets where the clusters are of differing size. Fuzzy c-means may, however, be successfully used for pre-processing to dimensionally reduce the data thus allowing a simpler RBF architecture.

The RBF network without fuzzy c-means pre-processing is very successful but leads to a more complex architecture.

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References

Ali, Z. O'Hare, W.T. Sarkodie-Gyan, T. Theaker, B.J. 1999: Gas-sensing system using an array of coated quartz crystal microbalances with a fuzzy inference system. J. Therm. Anal. Cal., 55 (2) 371-381.

Ali, Z. James, D. Scott, S.M. O'Hare, W.T. Rowell, F.J. 2003: Gas phase pre-concentration for a quartz crystal microbalance based electronic nose. J Therm. Anal. Cal., 71, 163 - 171.

Barko, G. Abonyi, J. Hlavay, J. 1999: Application of fuzzy clustering and piezoelectric chemical sensor array for investigation on organic compounds. Anal. Chim. Acta 398, 219-226.

Bezdek, J.C. 1981: Pattern recognition with fuzzy objective function algorithms. Plenum. N.Y.

Broomhead, D.S. Lowe, D. 1988: Multivariate functional interpolation and adaptive networks, Complex Systems. Vol. 2, 321-355.

Byun, H.G. Persaud, K.C. Khaffaf, S.M. Hobbs, P.J. Misselbrook, T.H. 1997: Application of unsupervised clustering methods to the assessment of malodour in agriculture using an array of conducting polymer odour sensors. Computers and Electronics in Agriculture, 17, 233-247.

Callan, R. 1999: The essence of neural networks. Prentice Hall.

Carey, W.P. Kowalski, B.R.1986: Chemical piezoelectric sensor and sensor array characterization. Anal. Chem. 58 3077-3084

Dunn, J. C. 1973: A fuzzy relative of the ISODATA process and its use in detecting compact well-separated clusters. J. Cybernetics. Vol. 3, no 3, 32-57.

Evans, P. Persaud, K.C. McNeish, A.S. Sneath, R.W. Hobson, N. Magan, N. 2000: Evaluation of a radial basis function neural network for the determination of wheat quality from electronic nose data. Sens.Acts. B, 69, 348-358.

Fang, M. Vetelino, K Rothery, M Hines, J. Frye, G.C. 1999: Detection of organic chemicals by SAW sensor array. Sens.Acts. B, 56 (1-2) 155-157.

Gardener, J.W. Bartlett, P.N. 1999: Electronic noses, principles and applications. Oxford University Press.

Gustafson, D.E. Kessel, W.C. 1979: Fuzzy clustering with a fuzzy covariance matrix. Proc. IEEE CDC, 761-766.

Hiserodt, R.D. Ho, C.T. Rosen, R.T. 1997: The characterization of volatile and semi-volatile components in powdered turmeric by direct thermal extraction gas chromatography mass spectrometry. ACS SYM SER, 660, 80-97.

Linusson, A. Wold, S. Norden, B. 1998: Fuzzy clustering of 627 alcohols. Guided by a

strategy for cluster analysis of chemical compounds for combinatorial chemistry. Chemometrics and Intelligent Laboratory Systems. 44, 312-227.

Llobet, E. Hines, E.L. Gardner, J.W. Bartlett, P.N. Mottram, T.T. 1999: Fuzzy ARTMAP based electronic nose data analysis. Sens. Act. B 61 183-190

Looney, C.G. 1997: Pattern recognition using neural networks. Oxford University Press.

Martin, Y.G. Pavon, J.L.P. Cordero, B.M. Pinto, C.G. 1999: Classification of vegetable oils by linear discriminant analysis of electronic nose data. Anal.Chim.Acta, 384, 83-94.

Miele, P. Marquis, F. 2001: One-sensor electronic olfactometer for rapid sorting of fresh fruit juices. Sens. Acts. B 76 470-476

Paulsson, J.P. and Winqvist, F. 1999: Extraction and selection of parameters for evaluation of breath alcohol measurement with an electronic nose. Foren.Sci.Int., 105, 2 (1), 95-114.

Persaud, K. and Dodd, G.H. 1982: Analysis of discrimination mechanisms in the mammalian olfactory system using a model nose. Nature, 299, 352-355.

Sauerbrey, G.Z. 1959: Verwendung von schwingquartzen zur wägung dünner schichten und zur mikrowägung. Z. Phys., 155, 206.

Scott, S.M. Ali, Z. O'Hare, W.T. 2003: Fuzzy logic and fuzzy classification techniques.

In Hugh M. Cartwright & Les M. Sztandera (eds). Soft Computing Approaches in Chemistry, Springer-Verlag. Heidelberg.

Stella, R. Barisci, J.N. Serra, G. Wallace, G.G. DeRossi, D. 2000: Characterisation of olive oil by an electronic nose based on conducting polymer sensors. Sens.Acts B, 63, 1-9.

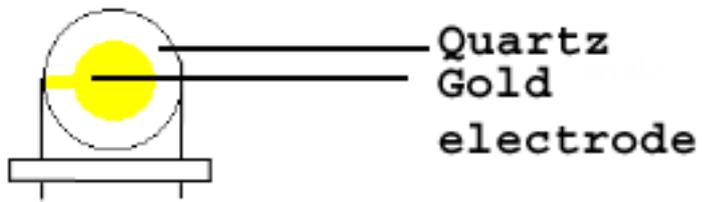


Figure 1 PZQ sensor

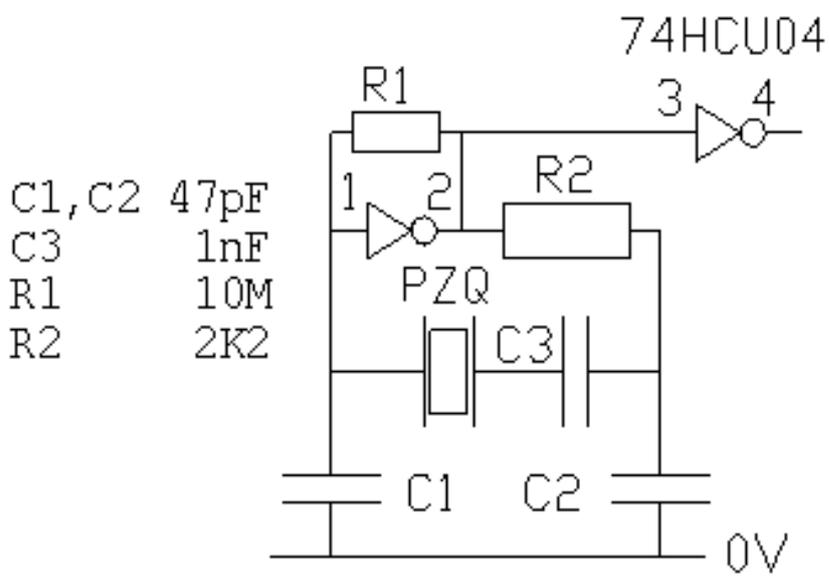


Figure 2 Oscillation circuit for PZQ

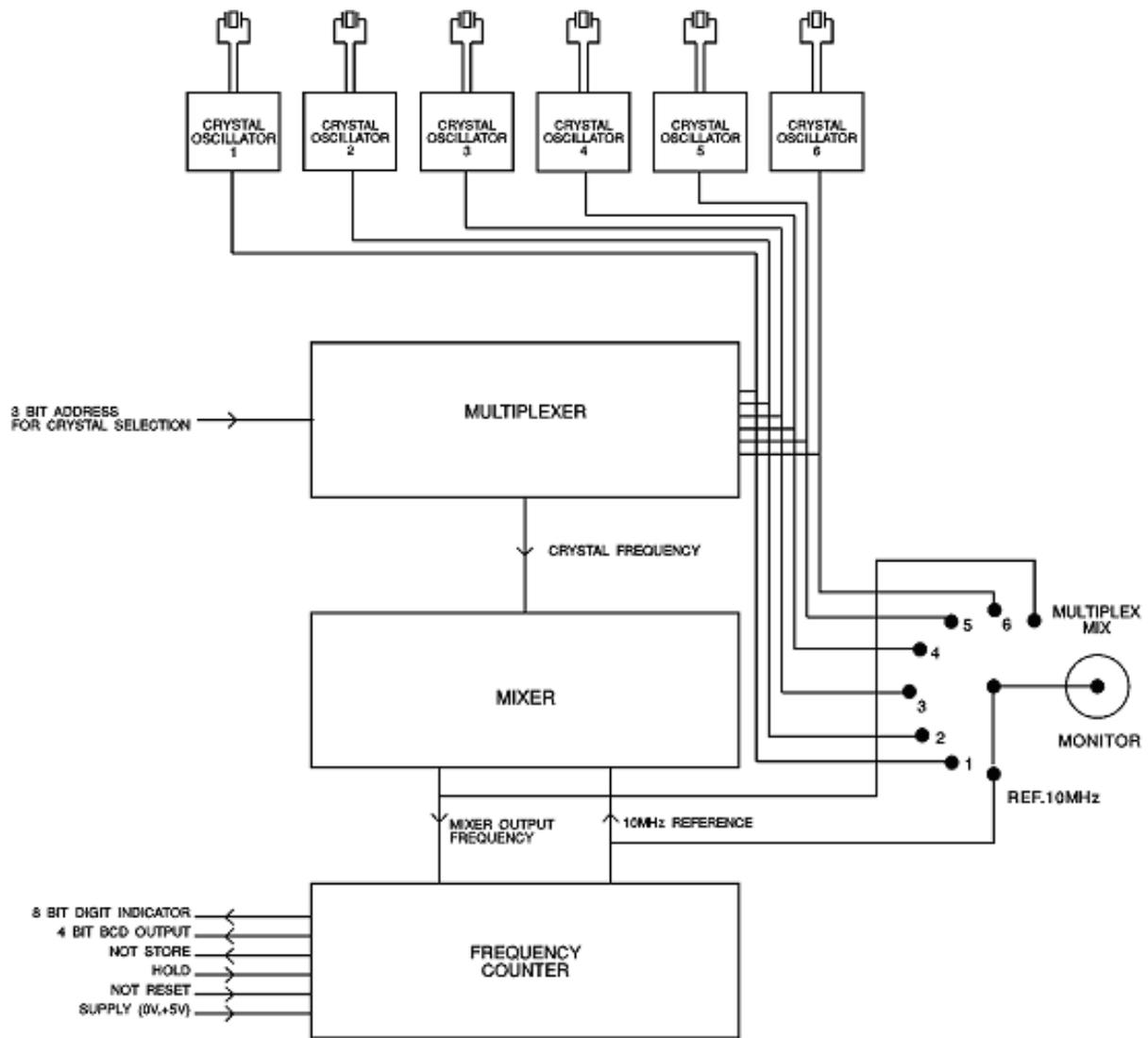


Figure 3 Block diagram of nose electronic circuit

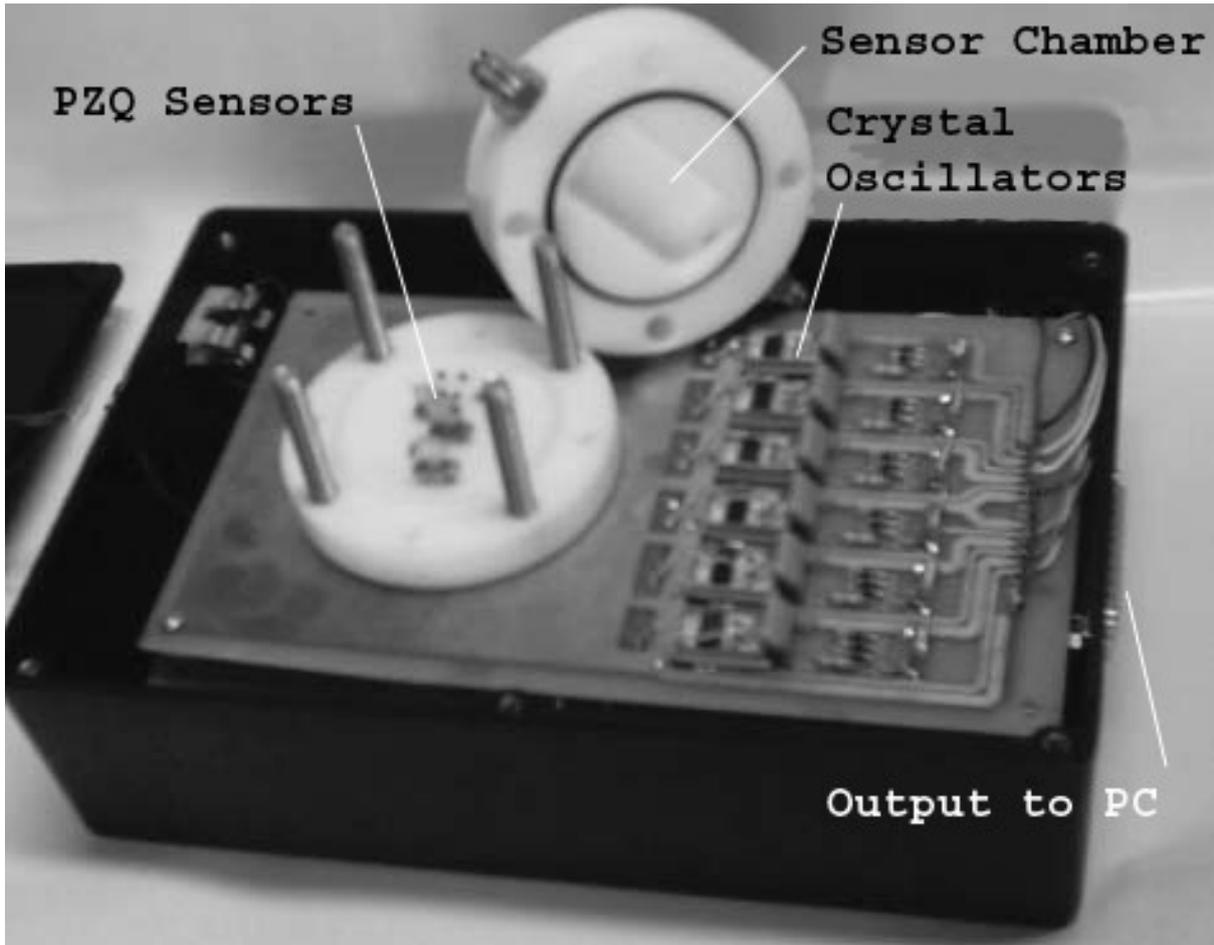


Figure 4 Photograph of nose system

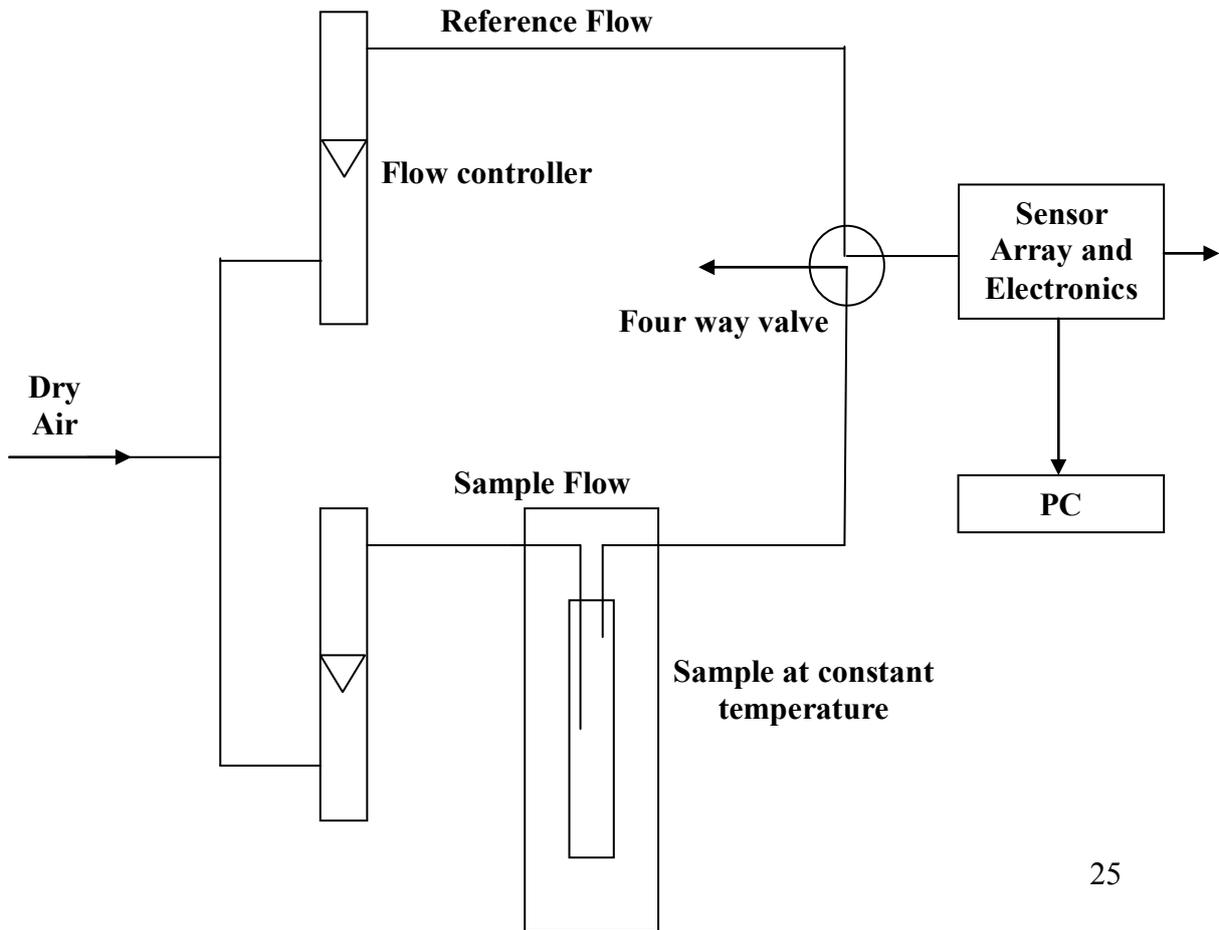


Figure 5 Block diagram of nose system

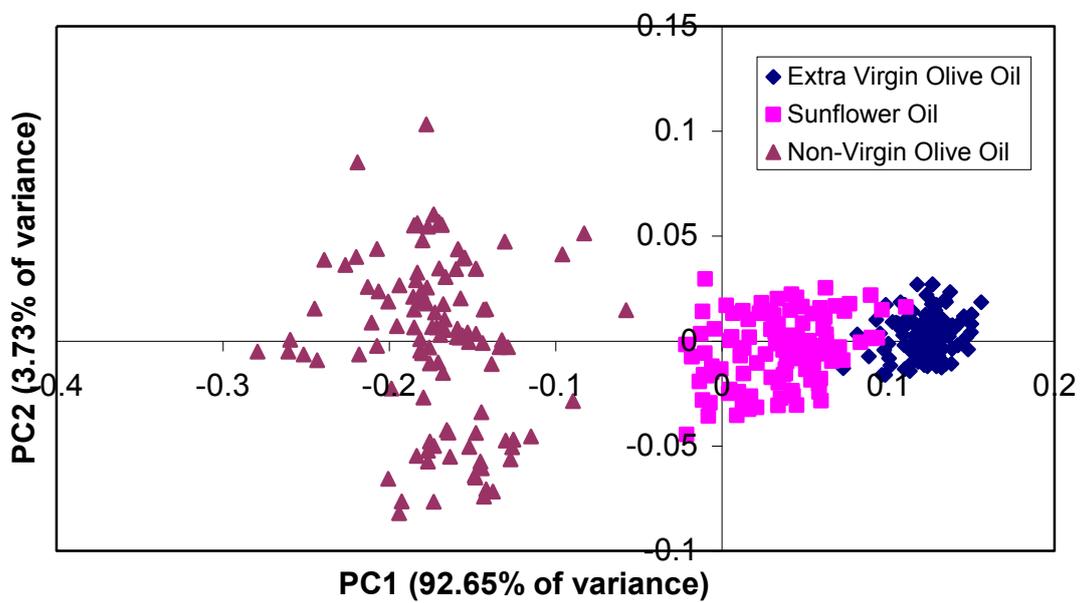


Figure 6 PCA scores plot for edible oil data

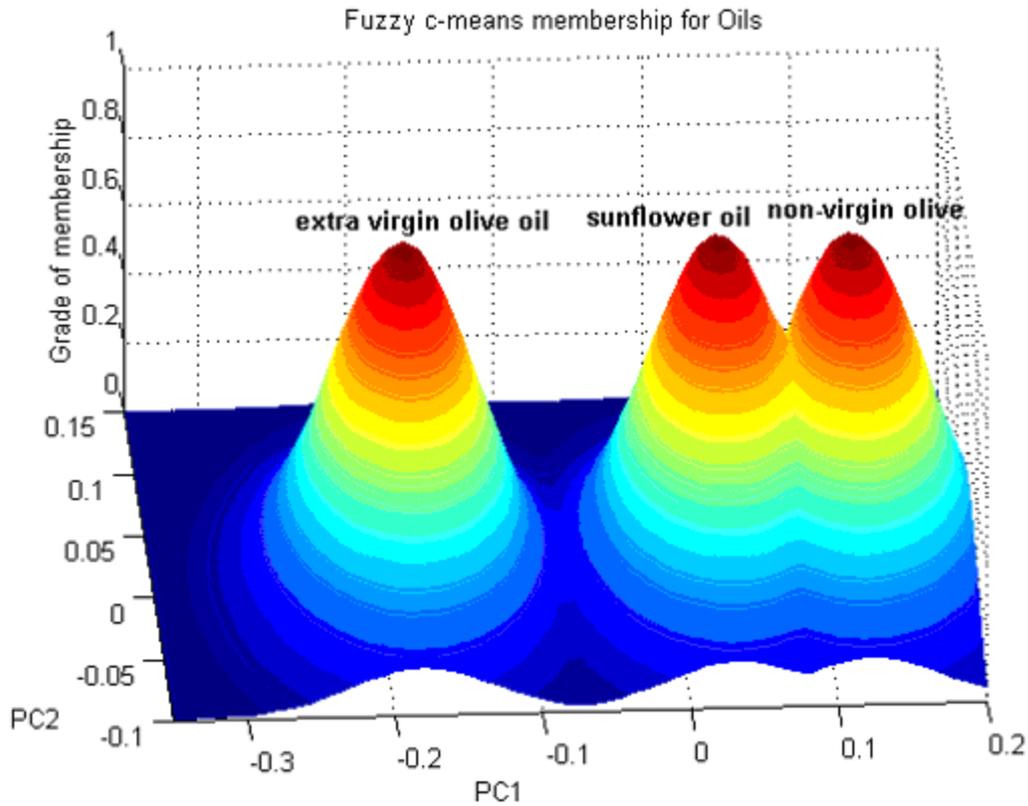


Figure 7 Fuzzy c-means memberships for edible oils

Table 1 Fuzzy c-means analysis results

Winning Category	Non Virgin Olive	Sunflower Oil	Extra virgin Olive Oil	Total	Correct (%)
Non virgin Olive	126	0	0	126	100
Sunflower	79	29	0	108	26.85
Extra Virgin Olive	0	11	101	112	90.17
			Total Correct	256	73.98

Table 2 RBF 6-6-3 Network (raw data input) results

Class	Non-Virgin Olive Oil	Sunflower Oil	Extra Virgin Olive Oil	Total	Correct (%)
Non Virgin Olive Oil	125	1	0	126	99.20
Sunflower	1	107	0	108	99.07

Extra Virgin Olive Oil	0	0	112	112	100
			Total Correct	344	99.42

Table 3 RBF 3-4-3 Network (Fuzzy c-means input) results

Class	Non-Virgin Olive Oil	Sunflower Oil	Extra Virgin Olive Oil	Total	Correct (%)
Non Virgin Olive Oil	126	0	0	126	100
Sunflower	16	92	0	108	85.18
Extra Virgin Olive Oil	0	0	112	112	100
			Total Correct	330	95.37