Development and Application of a New Low Cost Electronic Nose for the Ripeness Monitoring of Banana using Computational Techniques (PCA, LDA, SIMCA, and SVM)

Alireza SANAEIFAR[1], Seyed Saeid MOHTASEBI[1], Mahdi GHASEMI-VARNAMKHASTI[2], Hojat AHMADI[1] and Jesus LOZANO[3]

[1]Department of Agricultural Machinery Engineering, Faculty of Agricultural Engineering and Technology, College of Agriculture and Natural Resources, University of Tehran, Karaj, Iran;
[2]Department of Mechanical Engineering of Biosystems, Shahrekord University, Shahrekord, Iran;
[3]Research Group on Sensory Systems, University of Extremadura, Badajoz, Spain

Abstract

Sanaeifar A., Mohtasebi S.S., Ghasemi-Varnamkhasti M., Ahmadi H., Lozano J. (2014): **Development and application of a new low cost electronic nose for the ripeness monitoring of banana using computational techniques (PCA, LDA, SIMCA, and SVM)**. Czech J. Food Sci., **32**: 538–548.

Potential application of a metal oxide semiconductor based electronic nose (e-nose) as a non-destructive instrument for monitoring the change in volatile production of banana during the ripening process was studied. The proposed e-nose does not need any advanced or expensive laboratory equipment and proved to be reliable in recording meaningful differences between ripening stages. Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Soft Independent Modelling of Class Analogy (SIMCA) and Support Vector Machines (SVM) techniques were used for this purpose. Results showed that the proposed e-nose can distinguish between different ripening stages. The e-nose was able to detect a clear difference in the aroma fingerprint of banana when using SVM analysis compared with PCA and LDA, SIMCA analysis. Using SVM analysis, it was possible to differentiate and to classify the different banana ripening stages, and this method was able to classify 98.66% of the total samples in each respective group. Sensor array capabilities in the classification of ripening stages using loading analysis and SVM and SIMCA were also investigated, which leads to develop the application of a specific e-nose system by applying the most effective sensors or ignoring the redundant sensors.

Keywords: ripening; electronic nose; non-destructive; support vector machine; sensors

Banana is one of the most important fruits in the world in terms of production and consumption (Aurore *et al.* 2009). At the present time, bananas are cut at a mature-green stage and then exported to consumer countries, so on-line quality inspection of banana during ripening treatment is quite important to preserve a firm pulp texture, good colour, and flavour and also to prohibit from contusion (Soltani *et al.* 2011). After harvesting, fresh banana quickly changes and the colour, firmness, and flavour of the fruit are always damaged during storage (Boudhrioua *et al.* 2003). Maintaining the quality and approaching a sufficient price need an optimum ripening stage for banana fruits. During banana ripening time, the peel colour changes, the flavour develops and the pulp softens. Colour change from green to yellow is the first visible sign of ripening (Li *et al.* 1997). The pattern of ethylene production during ripening in banana fruit differs from other climacteric fruits, with a sharp rise and fall of ethylene production during the early climacteric rise of respiration (Liu *et al.* 1999). However, more than 250 volatile components have been identified in banana. Ethylene is the most important volatile component which constitutes about 50–75% of volatile components (Jayanty *et al.* 2002).

The bananas are usually kept in airtight warehouses in which a system is controlling ethylene gas. In other words, in commercial practice the quality of ripening could be controlled by ethylene treatment (Kesari *et al.* 2010). The ripening treatment of banana fruits has been progressed through an experimental procedure by the experience of trained labourers into a programmatic ethylene gas control manner. Although, this method has not completely achieved the uniform ripening of banana fruits yet, there was no monitoring system for detecting the ripening quality of banana fruits (Soltani *et al.* 2011). Different methods have been used to determine the ripening stages of banana but the techniques adopted are destructive including determination of pulp to peel ratio and firmness of the fruit (Ramma *et al.* 1999). Monitoring and controlling ripeness is a significant issue in the fruit industry since the state of ripeness during harvest, storage and market distribution defines the quality of the final product which is approved by customer satisfaction (Brezmes *et al.* 2000). Hence, technologies that classify the fruits according to their colour, texture, taste, flavour, and nutritive value would assure higher fruit quality and consistency, which in turn increases the consumer acceptance and satisfaction. The processing industry also competes with higher profitability (Lu & Ariana 2002). For measuring these properties, some instrumental methods are used which are mostly destructive and manual work is involved in. The non-destructive measurement of the fruit internal quality is becoming important for the consumers and the industry as a whole (Rajkumar *et al.* 2012).

The e-nose is an instrument which imitates the sense of smell (Peris & Escuder-Gilabert 2009; Ghasemi-Varnamkhasti *et al.* 2011a). The device is designed to detect and discriminate among complex odours using an array of chemical sensors (Lozano *et al.* 2008). Under the influence of an odour stimulus, the sensor array generates a characteristic fingerprint or a smell print. The response of the sensor array presents an electronic fingerprint characteristic of each sample (Ghasemi-Varnamkhasti *et al.* 2011b). The sum of all these fingerprints provides a recognition pattern, so that the qualitative analysis can be done by help of an appropriate multivariate analysis tool based on these patterns (Alcañiz *et al.* 2012). Such characteristics greatly facilitate the application of the e-nose in fast monitoring of the volatile components of fruit, providing real-time information. In the literature there are several studies reporting the use of the e-nose in assessing fruit quality and ripening (Brezmes *et al.* 2000; Costa *et al.* 2003), and some experiments have been performed for apples (Di Natale *et al.* 2001; Saevels *et al.* 2004; Li *et al.* 2005), peaches (Benedetti *et al.* 2008; Zhang *et al.* 2008) and tomatoes (Berna *et al.* 2004; Gómez *et al.* 2008). Gómez *et al.* (2006a,b) investigated a change in the volatile production of ripeness states (unripe, half-ripe, full-ripe, and overripe) of tomato and mandarin, using an e-nose with ten different MOS sensors. The e-nose could differentiate among the ripeness states of tomato with 100% correct classification, and among the ripeness states of mandarin with 92% correct classification.

There are few researches concerning the use of an e-nose for analysing the banana ripening. A metal oxide semiconductor (MOS) sensor based system was used by Llobet *et al.* (1999) to calculate the performance of a neural network-based e-nose in determining the banana ripeness. The system was simple and ripening standard conditions in warehouse were not considered.

The purpose of this study was: (1) to fabricate and evaluate the capability of a new low-cost e-nose based on a sensor array of six MOS to classify bananas at five different ripening stages and to monitor their ripeness states in airtight warehouses, aiming to apply the e-nose system to an automatic control system for the ripening of banana fruits; (2) to study principal component analysis (PCA), linear discriminant analysis (LDA), support vector machines (SVM), and soft independent modelling of class analogy (SIMCA) techniques to determine whether the e-nose would be able to distinguish different ripening stages; (3) to address the discrimination ability of different sensors of sensor array at different ripening stages.

MATERIAL AND METHODS

Experimental material. Banana fruits (cv. Cavendish) imported from the Philippines were used in this research. The banana fruits had been stored at 14°C during transportation and then were stored in an airtight warehouse. Banana ripening is completed within 4 days. On the first day, fruits are stored at 20°C, and on the second day, ethylene is injected. On the third day, ethylene is removed and the temperature is decreased to 18°C and finally the temperature was decreased so that it would reach 11°C on the fourth day. Controlling temperature, humidity and ethylene gas concentration in the ripening room is very important. Bananas were kept in the warehouse at the humidity level of 85–88% for 4 days, as this

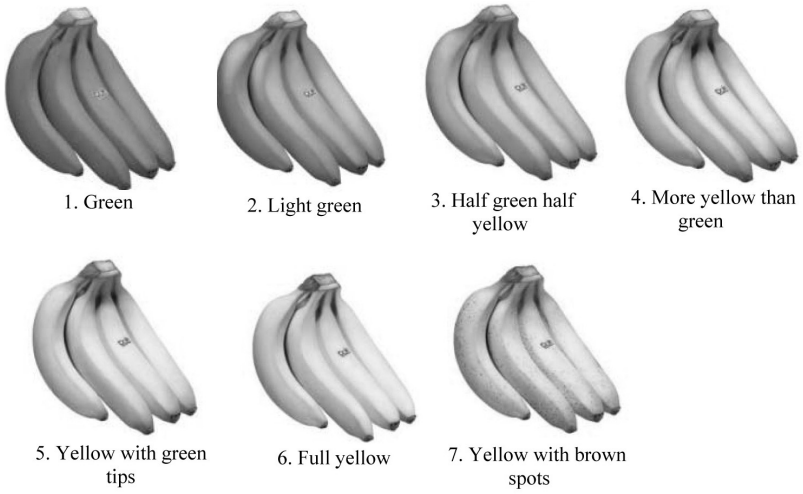

Figure 1. Colour chart of banana fruits in various stages

time period is needed for completing the ripening treatment of fruits. At this site, ripeness is currently assessed visually by comparing the peel colour of banana with standardised colour charts describing various stages of ripening. In commercial markets, seven ripening stages of bananas are usually considered as illustrated in Figure 1 (Banana Retail Guide of Del Monte Tropical Fruit Co., USA). Stages 6 and 7 are not performed in the warehouses and at the end of stage 5 the fruits are transported to the market. Before entering the warehouse, bananas are in the first ripening stage and after leaving the warehouse they are in the fifth ripening stage.

For performing the experiments, 15 bananas of the same size, weight and ripening stage were daily transferred from the warehouse to the laboratory in December 2012. Then e-nose tests were done on the samples till the fifth ripening stage. Moreover, all the measurements were performed on the day of transferring from the warehouse.

Experimental set-up

The e-nose consists of: (1) a sampling system (gas headspace handling and delivery system), (2) an array of gas sensors, (3) signal processing and conditioning (data acquisition system), and (4) an appropriate pattern recognition algorithm.

Sampling system. Eliminating undesirable factors influencing sensor responses leads the sampling system to provide a stable and reproducible headspace gas sampling environment (Falcitelli *et al.* 2002). The experimental set-up is shown in Figure 2. It consists of two separate chambers for the sampling system: a sample chamber and a sensor chamber. There are different parts inside this system including one air pump, tubes, and several electrovalves. The fruit is placed in the sample chamber for gathering adequate gas. The volume of this chamber is 2 l and its main purpose is to accumulate all the aromatic compounds which the fruit releases during the extraction phase. The volume of the sensor chamber including the sensor array is 1.4 l.

The measurement process is divided into three different phases: concentration, measurement, and desorption. Depending on the measurement phase of the system, the air is directed through different circuits by the electrovalves controlled by a computer program. All experiments were conducted at the temperature of 25°C and 25–35% RH, and the

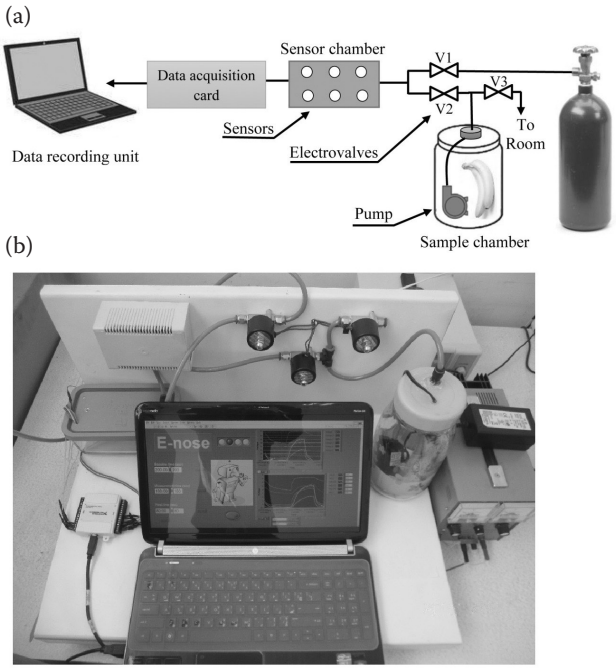

Figure 2. (a) Schematic view and (b) experimental setup of the e-nose system

Table 1. Gas sensor array of the e-nose

Name	Main applications	Typical detection ranges (ppm)
MQ-3	alcohol	0.05–10
MQ-5	LPG, natural gas, coal gas	200–10 000
MQ-9	CO and combustible gas	20–2000 (carbon monoxide), 500–10 000 (CH_4), 500–10 000 (LPG)
MQ-131	ozone	10–1000
MQ-135	air quality control	10–10 000 (ammonia, benzen, hydrogen)
MQ-136	sulphureted hydrogen	1–200

temperature was maintained constant to the nearest ± 1°C.

The measurement procedure starts by placing two bananas in the sample chamber. Preliminary experiments showed that the headspace reached a steady state after 1800 s of equilibration, so that experiments were conducted after 1800 s of equilibration and were designed to strengthen the aromatic concentration to obtain higher sensor responses. When the concentration phase ends, synthetic air is passed over the sensors for 200 s to reach their baseline values. Valve 1 is open during this period of time.

Then the measurement phase starts and continues for 180 s, which is enough for sensors to reach a stable value. In this phase the headspace gas was carried to the sensor chamber using a pump (the flow rate was 1.3 l/min). During the measurements process valve 2 is open and valves 1 and 3 are closed. The desorption phase, which was considered for 80 s, was activated as the measurement was completed. Its main purpose was to remove the odour molecules and to clean or desorb the sensors by use of synthetic air in such a way that the sensors could go back to their baseline values. In this phase, valve 2 is closed and valves 1 and 3 are open and the air existing in the sample chamber is exhausted by the pump. Right after that, a new measurement is started as the concentration phase could start. On the computer screen, the experimental data was displayed in real time and stored as text files on a disk for data processing.

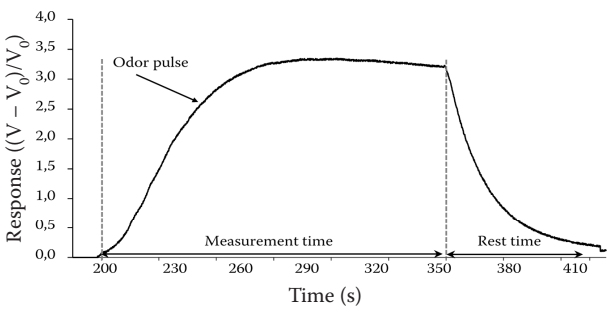

Figure 3. Aroma fingerprint of MQ-135 sensor

Using specially designed software and computer-based data acquisition and automated operations, the entire measurement phases were controlled. Features like programmable sequence control, dynamic fingerprint display, data logging, data archival, etc. were provided through the software. The software was developed in LabView (National Instruments, Austin, USA). For instance, the aroma fingerprint of MQ-135 sensor is shown in Figure 3 depicting different working phases.

Sensor array. Volatiles gases in the set-up were assessed using an array of metal oxide semiconductor (MOS) sensors. A set of six gas sensors (Hanwei Electronics Co., Ltd., Henan, China) was placed in a cycloid chamber. To reach the working temperature according to the manufacturer's operating data sheets (300–500°C), the sensors were heated by applying 5V DC voltage to their heater resistance. The sensor array used in the system is shown in Table 1.

Data acquisition system. The e-nose was comprised of a data acquisition card (NI USB-6009, National Instruments Corporation, Austin, USA). Through the data acquisition card, the sensor responses were stored in the computer and these data sets were analysed to extract information. Signal preprocessing is the extraction of relevant data from the responses obtained and preparation of the data for a multivariate pattern analysis (Wall *et al.* 2003). The major aspects of this preprocessing are: (a) baseline identification and manipulation/determination, (b) compression, and (c) normalisation. The first stage of preprocessing includes manipulating the sensor response with respect to its baseline (e.g. response to a reference analyte) for the purposes of drift compensation, contrast enhancement, and scaling. Differential, relative, and fractional techniques are three different techniques for the baseline manipulation. Fractional methods for MOS chemo-resistors are also widely used (Gutierrez-Osuna *et al.* 2002). In these methods the baseline is subtracted and then divided from the sensor response. Fractional methods were used in the present study.

Compression (Pan *et al.* 2008) is a preprocessing stage in which the response of the sensor array is utilised as a feature vector or a fingerprint by decreasing the number of descriptors. In this study, the maximum response values for each sensor were individually extracted and analysed. Normalisation is the final stage of preprocessing. Normalisation techniques are applied to operate on the sensor signals to compensate for sample-to-sample variations due to the change in analyte concentration and drift in the sensors. Alternately, the entire database of a single sensor can be operated upon and scaling of sensors can be effected (Bhattacharyya & Bandhopadhyay 2010). In this research, the range scale was used to restrict data between –1 to 1 as shown in Eq. (1) (Scott *et al.* 2007):

$$A_{ij} = \left(2 \frac{A_{ij} - \min(A_j)}{\max(A_j) - \min(A_j)}\right) - 1 \quad (1)$$

where: A_{ij} – i^{th} sample of the j^{th} sensor; A_j – contains all n responses of samples for sensor j

Data analysis methods. The values of the sensor array were used together with quality parameters in statistical analysis. For monitoring the ripening process, principal component analysis (PCA), and linear discriminant analysis (LDA) were applied. LDA, as a supervised method, has been used for feature extraction and variable selection (Maugis *et al.* 2011) in a dataset like the unsupervised principle component analysis (PCA).

Soft independent modelling of class analogy (SIMCA) and support vector machine (SVM) were used in this study as follows.

SIMCA is based on making a PCA model for each class in a defined training set. SIMCA is known as a supervised pattern recognition method as the individual PCA models define classification rules. An object is fitted and classified in a class when the SIMCA distance to the model is low in comparison with the residual standard deviation of the class, the number of principal components used for each class may be present or may be selected in such a way that they explain a given percentage of the variance of the data. In this way, a closed space is constructed at a significance level of 95% by a critical distance. Applying the SIMCA technique to the data is the most complicated as it is based on the principal components of each category and critical distances with probabilistic significance (Peña *et al.* 2002). To display the response of an e-nose to simple and complex odours, this technique has been widely used by researchers and it provides qualitative information for e-nose pattern recognition files (Ghasemi-Varnamkhasti *et al.* 2012; Li *et al.* 2012).

SVM, which is based on statistical learning theory (SLT), has been recently introduced as a new technique for solving a variety of learning classification and prediction problems (Cristianini & Shawe-Taylor 2000). SVM was originally developed for the linear classification of separable data, but is applicable to nonlinear data with the use of kernel functions.

Separating the classes by the particular hyperplane, which maximises a quantity called margin, is the main idea of SVM. The margin is the distance from the nearest point in the dataset to a hyperplane separating the classes. A kernel function is used to map from the original space to the feature space. This function can appear in many forms, providing the ability to apply nonlinear classification cases. The kernels are possibly observed as a mapping of nonlinear data to a higher dimensional feature space, while providing a computation shortcut by allowing linear algorithms to work with such a feature space. The support vector is defined as the reduced training data from the kernel. When some classes are inhomogeneous and partly overlapping, SVM will perform well and thus, building local PCA models with all samples will not be successful because one class may encompass other classes if all samples are used. SVM has some advantages over other classification methods, as it has a unique solution, and has a lower tendency of overfitting compared to other nonlinear classification methodologies. Of course, the model validation is the critical aspect in preventing overfitting for any method. For modelling of nonlinear data SVMs are effective, and they are relatively insensitive to variation in parameters. SVM uses an iterative training algorithm to achieve discrimination among different classes (Gualdron *et al.* 2007).

The software of SPSS Statistics 21.0 (IBM, New York, USA) and the Unscrambler 10.2 (CAMO AS, Trondheim, Norway) was used for these analyses.

RESULTS AND DISCUSSION

E-nose response to banana aroma and signal analysis. Figure 4 shows a typical response of six sensors during the measurement of a banana sample. The data obtained are the fractional change in voltage $(V - V_0)/V_0$, where: V_0 – voltage of the sensors when the synthetic air blows over the sensor array. Each curve represents a different sensor response. As the figure shows, during the measurement of banana samples the curve increases exponentially and then

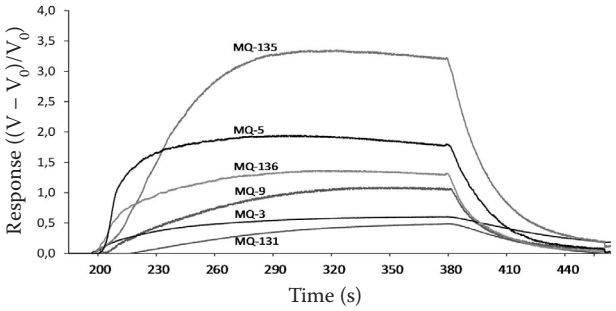

Figure 4. Typical response curves of the sensor array to banana aroma

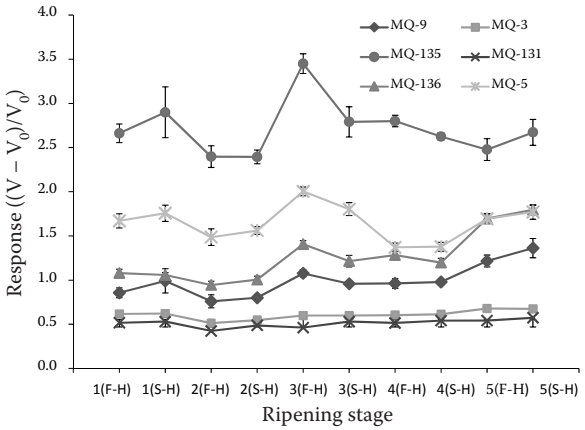

Figure 5. Fractional voltage of each sensor versus ripening stage

decreases to a level commensurate with the level of response determined by the odour in the synthetic air. It can be observed that, after an initial period of low and stable voltage which lasted 200 s (when only the clean air was crossing the sensor chamber), the voltage increased sharply.

The evolution of the signals generated by the sensor array is shown in Figure 5. During the banana fruit ripening process in the warehouse, each ripening stage was investigated during one day, from morning to night, thus changes in each half of the day are seen in this figure. Each line represents the average signal variation of 15 measurements for one sensor of the array (six sensors). Seven measurements were done in the first half of the day and 8 measurements were done in the second half of the day – (F–H) and (S–H) represent the first and the second half of the day, respectively.

It is observed that sensor MQ-135 exhibited higher values as compared with the data obtained from the rest of the sensors. By advancing and increasing the ethylene release during banana ripening, exogenous ethylene accelerates fruit ripening (Pathak *et al.* 2003; Barry & Giovannoni 2007). The specific aroma of each fruit is not related to the concentration of its volatile components. It is possible that the concentration is low but the aroma is considerable as it could be smelt. In climacteric fruits the amount of these compounds is increased as the fruit is ripening. The aromatic components in green, ripe and full-ripe bananas are 2-hexenal, eugenol and isopentanol, respectively (Salunkhe *et al.* 1976).

The lowest values of sensor responses were obtained at the second ripening stage, and increased as the ripening was completed. It seems that the increase in the sensor array response at the third ripening stage is caused by ethylene injection in the warehouse which played an important role in respiration acceleration (Tassoni *et al.* 2006). Although the sensor array responses increased in the second half of the day for other ripening stages, the responses decreased in the second half of the day at the third ripening stage.

PCA and LDA analysis. In order to see whether the chemical sensor array was able to distinguish between different ripening states, PCA and LDA analyses were applied to the 75 measurements performed with the e-nose, 15 measurements for each

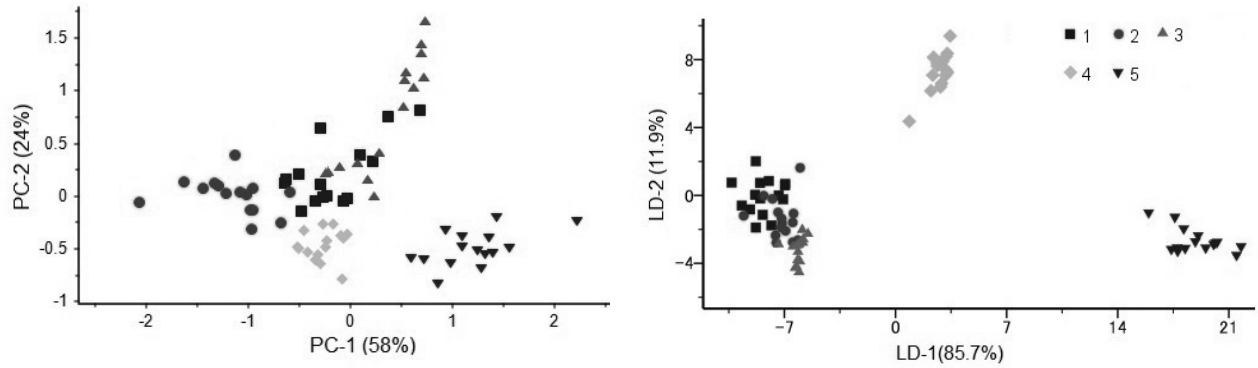

Figure 6. Scatter plot of the first two main axes illustrating the e-nose sensor array response data categorised into five groups for each ripening stage: (a) PCA and (b) LDA

Table 2. Discriminatory power values of the sensor array of the proposed e-nose

Discriminated classes	MQ-9	MQ-3	MQ-135	MQ-131	MQ-136	MQ-5
1–2	7.484033	7.481984	7.141355	7.392522	3.581411	4.512291
1–3	18.7098	10.35823	29.35484	21.75923	41.59697	26.1826
1–4	66.789	56.68409	72.54668	61.65113	84.21691	70.26456
1–5	64.91059	74.10889	45.30543	104.6043	43.37575	36.08348
2–3	10.41473	6.709987	15.32136	6.204248	17.26648	18.27372
2–4	34.94325	7.586401	22.59038	11.57252	33.20777	28.38242
2–5	22.84031	45.56417	20.48358	56.81172	42.81261	31.56839
3–4	61.03899	62.73805	58.18138	56.72617	56.10542	58.75363
3–5	42.85134	35.73695	46.25109	77.07547	59.38062	40.26561
4–5	41.32211	19.35687	42.33604	54.96688	41.52987	29.60231

group. PCA and LDA results are shown in Figure 6. This figure represents results of the analyses on a two-dimensional plane, principal component 1 (PC1) and principal component 2 (PC2) in Figure 6a and the first and the second linear discriminant LD1 and LD2 in Figure 6b.

By PCA, groups of stage 5 are clustered on the right of the plot, samples form stages 1, 3, and 4 are located in the middle of the plot. Figure 6a shows a partial overlapping between stage 1 group and stage 3 group, between stage 1 and stage 2 groups. The first two components, PC1 and PC2, contain 82% of data variance. The first principal component, PC1, explains 58% of the total variation, while 24% of the total variance is explained by PC2.

The results obtained by LDA provided a perfect classification. In this plot, about 97.6% of the total variance of the data is displayed. LD1 and LD2 accounted for 85.7% and 11.9% of the variance, respectively, classification accuracy obtained by LDA method with leave-one-out cross-validation was 97.3%. As the figure shows, ripening stage 5 is completely separated from the other groups and there is a partial overlapping between ripening stage 2 group and 1 and 3 groups.

Loading analysis. The loading analysis will help to identify the sensors responsible for discrimination in the current pattern file. The sensor might be switched off for analysis (the response signal was not used) if it has a rather smaller influence on the identification process. Sensors with loading parameters near to zero for a particular principal component have a low contribution to the total response of the array, whereas a discriminating sensor indicates high values. In Figure 7 the plot shows the relative importance of the sensors in the array. The loading factor associated to the first and second principal components for each sensor is represented.

Figure 7 shows that sensors MQ-136, MQ-5, and MQ-135 have a higher influence in the current pattern file, while sensor MQ-131 has a minor influence. There are sensor groups that have almost identical loading parameters and these could be represented by just one sensor. For example, sensors MQ-3 and MQ-9 have similar loading factors. Sensors with loading parameters near to the dilution factor for a particular principal component also made a small contribution to the total response of the array. Hence, a subset of few sensors could be chosen to explain nearly all variance. This result could be used in further studies to optimize the number of sensors.

SIMCA. Besides methods used in evaluating the classification of banana ripening stages, the SIMCA method was also used which obtained an acceptable classification accuracy of 92%. As shown in Figure 6, in PCA, there is a partial overlapping between classes 1 and 2 as well as existing overlapping between classes 1 and 3. Figure 2 obtained by SIMCA method was used to discover the sensor role in class differentiation. The discrimination power of a sensor indicates the ability of that sensor to discriminate between two stages of

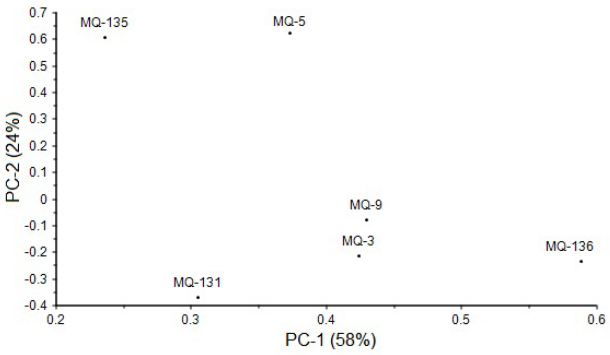

Figure 7. Loading analysis related to PC1 and PC2 for banana

ripening. Thus, a sensor with a high discrimination power (with regard to two particular stages) is very important for the differentiation between the two corresponding stages.

As Table 2 shows, all sensors had a low power in discriminating between classes 1 and 2, however sensor MQ-136 had the highest discrimination power for discriminating class 1 and 3. It was possible to conclude that this sensor played a considerable role in discriminating between these two classes in PCA. Sensor MQ-131 had clearly the highest discrimination power in discriminating between classes 1 and 5, and sensor MQ-136 had the lowest discrimination power to discriminate between classes 1 and 2. Considering Table 2, the highest value of MQ-3 sensor was obtained in discriminating classes 1 and 5 which were related to green and ripe banana, respectively. MQ-3 sensor is responsible for the alcohol aroma concentration. Therefore, it can be concluded that during banana ripening, a change in the alcohol concentration is high. This conclusion closely agrees with the literature (Yang *et al.* 2011). Aroma changes caused by ripening are complicated, so understanding the importance of each sensor in e-nose sensors may help to elaborate ripening stages.

The first class distance from different ripening stages representing green banana is shown in Figure 8. As it is observed in this figure, the distance between classes 1 and 2 is very small, indicating small changes between green banana and banana which is one day after ripening. Classes 1 and 5 had the largest difference between various classes and these two classes were completely discriminated from each other.

SVM. For classification, a supervised pattern recognition method called SVM was applied. SVM was used to test the ability of the e-nose set-up to discriminate between ripening stages. Two SVM classification types, c-SVM and nu-SVM which are also known as Classification SVM Type 1 and Classification SVM Type 2, are available which are based on different means of minimizing the classification error function. A capacity factor, C, can be defined in the c-SVM classification. The value of C should be chosen based on the knowledge of the noise in the data being modelled. Its value can be optimised through cross-validation procedures. When the nu-SVM classification is used, the nu value must be defined. Nu serves as the upper bound of the fraction of errors and is the lower bound for the fraction of support vectors. More errors occur as nu increases, while the margin of class separation increases (Fan *et al.* 2005).

The kernel type to be used as a separation of classes can be chosen from the following four options: linear, polynomial, radial basis function, sigmoid. Different kernel functions were tested for checking the robustness of the classifier model. The radial basis function is also a simple function and can model systems of varying complexity. The radial basis kernel function was eventually used for this study to project the training data to a space that maximised the margin hyperplane. The optimal regularisation parameter of the SVM was set to nu = 0.255. This value was experimentally found by minimising the leave-one-out error over the training set, which provides an estimate of the generalisation performances of the final classifier. The kernel parameters and the value of the constant nu determine the complexity of the SVM solution and hence, its generalisation ability. A leave-one-out cross-validation method was used to evaluate the performance of the final SVM. Given 75 measurements, the model was trained 75 times using 74 vectors. Afterwards, the vector left out was used for testing the model. Performance in training was estimated as the averaged performance over the 75 tests.

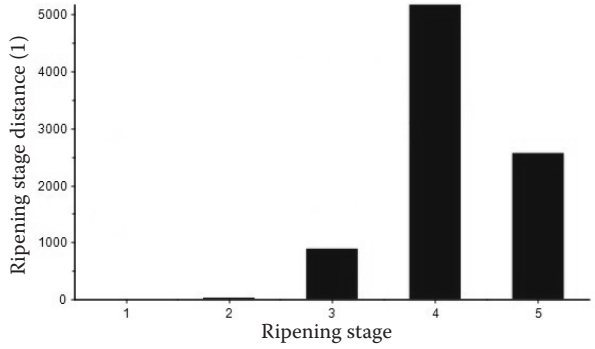

Figure 8. First stage distance from different banana ripening stages

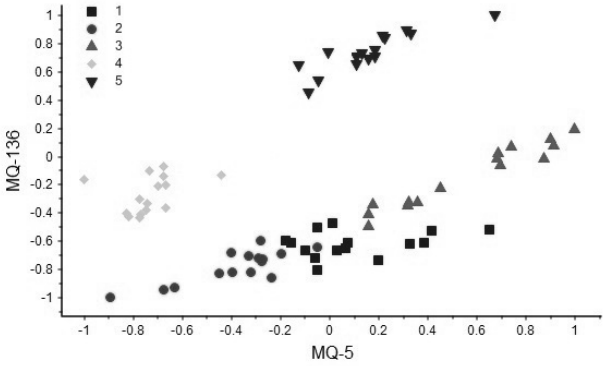

Figure 9. Pairs of sensors which made the best discrimination

A very good success rate in classification was obtained in the ripening classification of banana, accuracies of training and validation were found to be 100 and 98.66% respectively.

SVM is useful to see for which combinations of pairs of sensors there is a good discrimination between the classes. Pairs of sensors which made the best discrimination between various classes are shown in Figure 9. Sensors MQ-5 and MQ-136 provided the best combination of sensors for discriminating various ripening stages. This leads to choose a minimum quantity of sensors for optimum discrimination between classes in order to decrease costs.

CONCLUSION

In this research, a new low cost MOS-based e-nose was designed to recognise the fruit ripeness stages. The potential of the e-nose to monitor changes in aroma fingerprint during ripening was studied. The application did not require any advanced or expensive laboratory equipment and proved to be reliable in recording meaningful differences among ripening stages as it was also seen during data analysis and interpretation. The proposed e-nose offers a cheap and non-destructive instrument that can be operated by non-specialists. PCA, LDA, SVM and SIMCA were used to investigate whether the e-nose was able to distinguish between ripening stages. The SVM classification tool shows its superiority in solution to classification of ripening stages by e-nose data. The awareness of the sensor array capability could help us to make the appropriate decisions for selecting, changing, or even fabrication of the sensors relevant to the project purpose. By performing SIMCA, SVM, and loading analysis, the ability of the sensors was computed, and we concluded that the capability of the sensor array is acceptable for the ripening fingerprint detection. This result could be used in further studies to optimise the number of sensors.

References

Alcañiz M., Vivancos J.L., Masot R., Ibañez J., Raga M., Soto J., Martínez-Máñez R. (2012): Design of an electronic system and its application to electronic tongues using variable amplitude pulse voltammetry and impedance spectroscopy. Journal of Food Engineering, **111**: 122–128.

Aurore G., Parfait B., Fahrasmane L. (2009): Bananas, raw materials for making processed food products. Trends in Food Science & Technology, **20**: 78–91.

Barry C.S., Giovannoni J.J. (2007): Ethylene and Fruit Ripening. Journal of Plant Growth Regulation, **26**: 143–159.

Benedetti S., Buratti S., Spinardi A., Mannino S., Mignani I. (2008): Electronic nose as a non-destructive tool to characterise peach cultivars and to monitor their ripening stage during shelf-life. Postharvest Biology and Technology, **47**: 181–188.

Berna A.Z., Lammertyn J., Saevels S., Natale C.D., Nicolaï B.M. (2004): Electronic nose systems to study shelf life and cultivar effect on tomato aroma profile. Sensors and Actuators B: Chemical, **97**: 324–333.

Bhattacharyya N., Bandhopadhyay R. (2010): Electronic nose and Electronic Tongue. In: Jha S.N. (ed.): Nondestructive Evaluation of Food Quality. Springer Verlag, Berlin-Heidelberg: 73–100.

Boudhrioua N., Giampaoli P., Bonazzi C. (2003): Changes in aromatic components of banana during ripening and air-drying. LTW-Food Science and Technology, **36**: 633–642.

Brezmes J., Llobet E., Vilanova X., Saiz G., Correig X. (2000): Fruit ripeness monitoring using an electronic nose. Sensors and Actuators B: Chemical, **69**: 223–229.

Costa G., Noferini M., Fiori G., Orlandi A. (2003): Non-destructive technique to assess internal fruit quality. Acta Horticulture, **603**: 571–575.

Cristianini N., Shawe-Taylor J. (2000): An Introduction to Support Vector Machines and other Kernel-based Learning Methods. 1st Ed. Cambridge University Press, Cambridge.

Falcitelli M., Benassi A., Di Francesco F., Domenici C., Marano L., Pioggia G. (2002): Fluid dynamic simulation of a measurement chamber for electronic noses. Sensors and Actuators B: Chemical, **85**: 166–174.

Fan R.-E., Chen P.-H., Lin C.-J. (2005): Working set selection using second order information for training support vector machines. Journal of Machine Learning Research, **6**: 1889–1918.

Ghasemi-Varnamkhasti M., Mohtasebi S., Rodriguez-Mendez M., Lozano J., Razavi S., Ahmadi H. (2011a): Potential application of electronic nose technology in brewery. Trends in Food Science & Technology, **22**: 165–174.

Ghasemi-Varnamkhasti M., Mohtasebi S.S., Siadat M., Lozano J., Ahmadi H., Razavi S.H., Dicko A. (2011b): Aging fingerprint characterization of beer using electronic nose. Sensors and Actuators B: Chemical, **159**: 51–59.

Ghasemi-Varnamkhasti M., Mohtasebi S.S., Siadat M., Razavi S.H., Ahmadi H., Dicko A. (2012): Discriminatory power assessment of the sensor array of an electronic nose system for the detection of non alcoholic beer aging. Czech Journal of Food Sciences, **30**: 236–240.

Gómez A.H., Hu G., Wang J., Pereira A.G. (2006a): Evaluation of tomato maturity by electronic nose. Computers and Electronics in Agriculture, **54**: 44–52.

Gómez A.H., Wang J., Hu G., Pereira A.G. (2006b): Electronic nose technique potential monitoring mandarin maturity. Sensors and Actuators B: Chemical, **113**: 347–353.

Gómez A.H., Wang J., Hu G., Pereira A.G. (2008): Monitoring storage shelf life of tomato using electronic nose technique. Journal of Food Engineering, **85**: 625–631.

Gualdron O., Brezmes J., Llobet E., Amari A., Vilanova X., Bouchikhi B., Correig X. (2007): Variable selection for support vector machine based multisensor systems. Sensors and Actuators B: Chemical, **122**: 259–268.

Gutierrez-Osuna R., Nagle H.T., Kermani B., Schiffman S.S. (2002): Signal conditioning and preprocessing. In: Pearce T.C., Schiffman S.S., Nagle H.T., Gardner J.W. (eds): Handbook of Machine Olfaction: Electronic Nose Technology. Wiley-VCH, New York.

Jayanty S., Song J., Rubinstein N.M., Chong A., Beaudry R.M. (2002): Temporal relationship between ester biosynthesis and ripening events in bananas. Journal of the American Society for Horticultural Science, **127**: 998–1005.

Kesari R., Trivedi P.K., Nath P. (2010): Gene expression of pathogenesis-related protein during banana ripening and after treatment with 1-MCP. Postharvest Biology and Technology, **56**: 64–70.

Li C.Y., Heinemann P., Irudayaraj J., Peterson D. (2005): Detection of apple defects using an electronic nose and znose. In: 2005 ASAE Annual International Meeting, Tampa, USA, July 17–20.

Li M., Slaughter D.C., Thompson J.F. (1997): Optical chlorophyll sensing system for banana ripening. Postharvest Biology and Technology, **12**: 273–283.

Li S., Li X., Wang G., Nie L., Yang Y., Wu H., Wei F., Zhang J., Tian J., Lin R. (2012): Rapid discrimination of Chinese red ginseng and Korean ginseng using an electronic nose coupled with chemometrics. Journal of Pharmaceutical and Biomedical Analysis, **70**: 605–608.

Liu X., Shiomi S., Nakatsuka A., Kubo Y., Nakamura R., Inaba A. (1999): Characterization of ethylene biosynthesis associated with ripening in banana fruit. Plant Physiology, **121**: 1257–1265.

Llobet E., Hines E.L., Gardner J.W., Franco S. (1999): Non-destructive banana ripeness determination using a neural network-based electronics nose. Measurement Science and Technology, **10**: 538–548.

Lozano J., Arroyo T., Santos J.P., Cabellos J.M., Horrillo M.C. (2008): Electronic nose for wine ageing detection. Sensors and Actuators B: Chemical, **133**: 180–186.

Lu R., Ariana D.A. (2002): Near-infrared sensing technique for measuring internal quality of apple fruit. Transactions of the ASAE, **18**: 585–590.

Maugis C., Celeux G., Martin-Magniette M.L. (2011): Variable selection in model-based discriminant analysis. Journal of Multivariate Analysis, **102**: 1374–1387.

Natale di C.D., Macagnano A., Martinelli E., Paolesse R., Proietti E., D'Amicro A. (2001): The evaluation of quality of post-harvest oranges and apples by means of an electronic nose. Sensors and Actuators B: Chemical, **78**: 26–31.

Pan S.Y., Hsieh B.Z., Lu M.T., Lin Z.S. (2008): Identification of stratigraphic formation interfaces using wavelet and Fourier transforms. Computers and Geosciences, **34**: 77–92.

Pathak N., Asif M., Dhawan P., Srivastava M.K., Nath P. (2003): Expression and activities of ethylene biosynthesis enzymes during ripening in banana fruits and effect of 1-MCP treatment. Journal of Plant Growth Regulation, **40**: 11–19.

Peña F., Cárdenas S., Gallego M., Valcárcel M. (2002): Characterization of olive oil classes using a ChemSensor and pattern recognition techniques. Journal of the American Oil Chemists' Society, **79**: 1103–1108.

Peris M., Escuder-Gilabert L. (2009): A 21st century technique for food control: Electronic noses. Analytica Chimica Acta, **638**: 1–15.

Rajkumar P., Wang N., EImasry G., Raghavan G., Gariepy Y. (2012): Studies on banana fruit quality and maturity stages using hyperspectral imaging. Journal of Food Engineering, **108**: 194–200.

Ramma I., Beni Madhu S.P., Peerthum S. (1999): Postharvest Quality Improvement of Banana. Food and Agricultural Research Council, Reduit, Mauritius.

Saevels S., Lammertyn J., Berna A.Z., Veraverbeke E.A., Natale C.D., Nicolaï B.M. (2004): An electronic nose and a mass spectrometry based electronic nose for assessing apple quality during shelf life. Postharvest Biology and Technology, **31**: 9–19.

Salunkhe D.K., Do J.Y., Maga J.A. (1976): Biogenesis of aroma constituents of fruits and vegetables. Critical Reviews in Food Science & Nutrition, **8**: 161–190.

Scott S.M., James D., Ali Z. (2007): Data analysis for electronic nose systems. Microchimica Acta, **156**: 183–207.

Soltani M., Alimardani R., Omid M. (2011): Evaluating banana ripening status from measuring dielectric properties. Journal of Food Engineering, **105**: 625–631.

Tassoni A., Watkins C.B., Davies P.J. (2006): Inhibition of the ethylene response by 1-MCP in tomato suggests that polyamines are not involved in delaying ripening, but may moderate the rate of ripening or over-ripening. Journal of Experimental Botany, **57**: 3313–3325.

Wall M.E., Rechtsteiner A., Rocha L.M. (2003): Singular value decomposition and principal component analysis. In: Berrar D.P., Dubitzky W., Granzow M. (eds): A Practical Approach to Microarray Data Analysis. Kluwer, Norwell: 91–109.

Yang X., Song J., Fillmore S., Pang X., Zhang Z. (2011): Effect of high temperature on color, chlorophyll, fluorescence and volatile biosynthesis in green-ripe banana fruit. Postharvest Biology and Technology, **62**: 246–257.

Zhang H.M., Chang M.X., Wang J., Ye S. (2008): Evaluation of peach quality indices using an electronic nose by MLR, QPST and BP network. Sensors and Actuators B: Chemical, **134**: 332–338.

Received for publication February 23, 2014
Accepted March 31, 2014

Corresponding author:

Dr Seyed Saeid Mohtasebi, University of Tehran, College of Agriculture and Natural Resources, Faculty of Agricultural Engineering and Technology, Department of Agricultural Machinery Engineering, Karaj, Iran; E-mail: mohtaseb@ut.ac.ir