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Development of electronic nose for fruits ripeness determination

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Abstract

This paper presents the study of using an artificial olfactory system as a non-destructive instrument to measure fruit ripeness. The cultivar chosen for this study is *Harumanis* mango. This system comprises of an array of semiconductor gas sensors as well as data acquisition and analysis components. Readings taken from *Harumanis* mangoes of different ripeness over a period of time are used to train the system. Each stage of ripeness of the mangoes leaves a different pattern or fingerprint onto the sensors array. A principal component analysis (PCA) is used to define three distinct regions according to the state of ripeness of the *Harumanis* mango. Artificial Neural Network (ANN) is then trained to classify the data into the observed three stages of ripeness. The trained network is integrated into the system to allow mango ripeness differentiation.

Keywords: Sensors & Algorithm, Electronic nose, Fruit ripeness

1 Introduction

Sensory panels have been identifying odours for years, however human panels are subject to fatigue, inconsistencies and are not able to compare over long period of time [1]. In the agriculture industries, a systematic approach to determine the ripeness of fruits determination is vital because variability in ripeness is perceived by consumers as a lack of quality.

Most of the traditional methods to assess fruit ripeness are destructive, and hence not desirable. As an example, to test the firmness of a fruit, a force has to be applied which in turn will damage the fruit resulting in spoilt produce. Other methods include measuring levels of chemical components and parameters that are correlated to ripeness such as pH, sugars contents and ethylene contents [2]. Besides these destructive traditional methods, there are also non destructive approaches which have been developed. These methods include nuclear magnetic resonance (NMR), proton magnetic resonance (PMR), vision system and acoustics. But all of the methods listed above have their drawbacks.

Another popular non destructive method is the use of electronic noses. An electronic nose is an instrument which comprises an array of electronic chemical sensors with partial specificity and an appropriate pattern recognition system, capable of recognizing simple or complex odours [3]. It is based on the fact that flavour, odour and volatile compounds are recognized through the sense of smell. The ability to reliably measure and quantify factors such as impurities, taints and adulteration are the reasons why industries favour electronic nose in ensuring product quality consistency. It also holds many advantages over other methods which includes; (1) rapid, real-time detection of volatiles; (2) lower costs; and (3) automation.

In this study, neural networks have been used as the pattern recognition tool. It has been used extensively to perform pattern recognition and it has been reported to produce good performance for the classification of food stuff such as coffees [4], medicinal plants [5], and cigarette content [6]. This paper presents an electronic nose employing an array of eight sensors integrated with neural networks, which can accurately classify the ripeness of *Harumanis* mango.

2 Approach and Methods

2.1 Sensor system set-up

A batch of *Harumanis* mango was acquired from the Perlis State Department of Agriculture, and placed into the experiment chamber. The chamber contains two ventilation fans and a PCB comprising array of sensors. Figure 1 show this experimental set up. The fans are vital to control the air flow inside the chamber during the purging process. Each time new reading is to be taken, the existing air inside the chamber needs to be flush out to make sure the air is back to the background condition. The sensor system comprises of eight tin oxide gas sensors purchased from Figaro Engineering Inc. Japan (see table 1) and integrated into the chamber. In general, the resistance of the sensors will decrease when exposed to appropriate gasses or volatile organic compounds (VOC), and are sensitive enough to detect the smell of the *Harumanis.* Measurement is taken by alternating between taking the aroma samples of *Harumanis* for 300 seconds and purging out the air inside the chamber which takes about 60 seconds. Measurements were recorded over a period of ten days. Data acquisition and storage system uses LabVIEW software.

Figure 1: the experimental set-up used to analyze the aroma of Harumanis

Table 1: Metal oxide sensors used in the electronic nose

Sensor	Sensitive to
TGS 822	Alcohol, organic vapour
TGS 826	Ammonia detection
TGS 825	Hydrogen sulfide
TGS 2104	Air quality sensor for CO/HC
TGS 2620	VOC
TGS 2600	Air contaminant
TGS 2180	Water vapour
TGS 2106	Air quality sensor for NOx

This software was also used to build the graphical user interface (GUI) (please refer Figure 2), which functions as:

- Acquiring signal from the sensors by means of data acquisition (DAQ) card and display the data in a real time graph
- As a link to MATLAB, where online testing can be done
- Displaying the stages of ripeness of the *Harumanis* during the test.

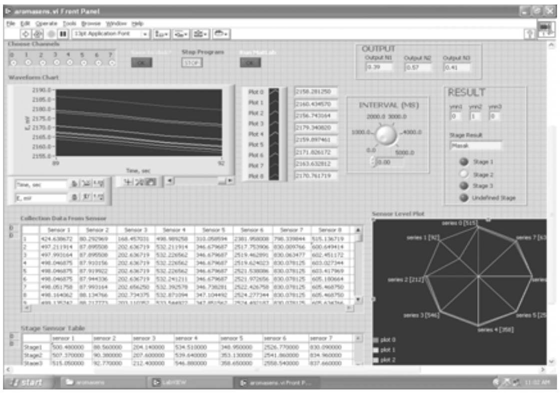

Figure 2: Graphical User Interface (GUI) for electronic nose system

2.2 Data clustering

The use of PCA to assess clustering within the data is now discussed. PCA is a linear method that has been shown to be efficient to distinguish the response of Electronic Nose. This algorithm helps to compress the vectors for each measurement and attain results that could be presented in simple two-dimensional plots.

The main purpose of this analysis is to set the stage according to the clusters obtained. The result of the PCA is described in Figure 3.

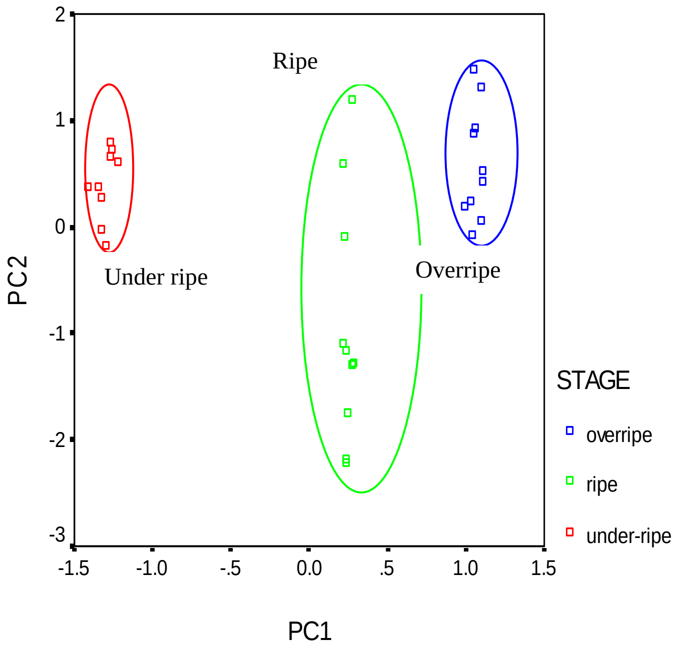

Figure 3: PCA plot

The results of the PCA show that the sensors are correlated, since 82% of the variance of the data is contained within the first principal component. The first two components can be used to represent 95% of the data variance (PC1 and PC2 accounted for 82% and 13% respectively). It can be observed that three distinct groups of stage of ripeness which correspond to under ripe, ripe and overripe are well discriminated.

2.2 Implementation of Artificial Neural Networks

The collected data is stored in one database. This database is then used to train the artificial neural network (ANN) which performs the pattern recognition function. The ANN was implemented in MATLAB. A three layer feedforward Multilayer Perceptron (MLP) was employed in the neural network architecture. The multilayer feedforward ANN was adopted in this project due to its relative simplicity and established capability. The optimum structure of neural network was determined by a trial and error method. Network outputs of different numbers of hidden neuron in the hidden nodes together with the sum square error (SSE) were analyzed. The number of hidden neurons that give the lowest SSE and the most accurate output would be used as the optimum size in the hidden layer. There are eight input neurons which correspond to the number of sensors and there are three networks to be trained as three stages of ripeness have been defined.

The stages that have been defined are under ripe, ripe and overripe. Hyperbolic tangent activation functions were used for neurons in the hidden layer while for output nodes, sigmoid activation function is used. The generated weights were then applied the GUI. During testing, the data acquired from sample were propagated to the neural networks in MATLAB through LABVIEW, and the detected stage together with the final neuron output reading will be displayed.

3 Results & Discussions

The experiment was conducted in a period of ten days starting from the under ripe stage until they are over ripe. The ripening of the fruits was accelerated to accommodate the relatively short test period. The response of the sensors was analyzed using Microsoft Excel. Figures 3, 4 and 5 depict the response of electronic nose at different stages of mango ripeness. Each curve represents the conductance transient of a single sensor in the concentration of *harumanis* aroma.

These responses actually give a unique pattern or fingerprint for each stage of ripeness. A database had been built up and used to train the artificial neural network. The total numbers of data used are 2700, and were divided into training and validation. To avoid over training, the sum square error has been monitored throughout the training process.

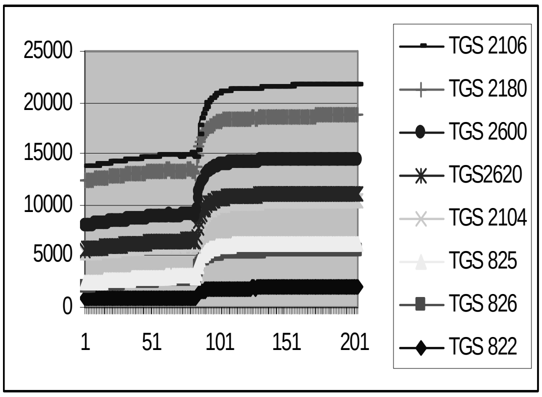

Figure 3: Sensor response for under-ripe mango

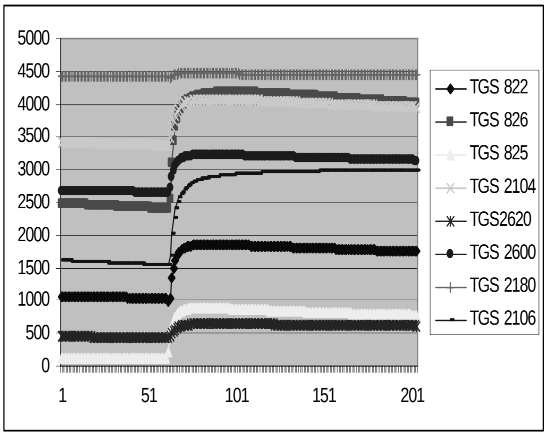

Figure 4: Sensor response for ripe mango

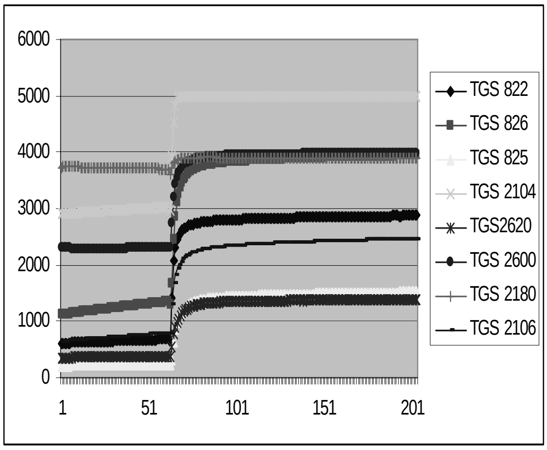

Figure 5: Sensor response for overripe mango

4 Conclusion

Based on the study conducted, it has been proven that this electronic nose system is capable of determining fruit ripeness. The sensor array successfully leaves a characteristic pattern or fingerprint for each stage of ripeness. And, the neural network which uses the multilayer perceptron (MLP) structure and Back Propagation (BP) algorithm was also proven as a capable pattern recognition tool, since it convincingly able to classify the *Harumanis* according to their stages of ripeness correctly.

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