Classification of Beverages Using Electronic Nose and Machine Vision Systems

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***Abstract*— In this work, the classification of beverages was conducted using three approaches: by using the electronic nose alone, by using the machine vision alone and by using the combination of electronic nose and machine vision. A total of two hundred and twenty eight beverages from fifteen different brands were used in this classification problem. A supervised Support Vector Machine was used to classify beverages according to their brands. Results show that by using the electronic nose alone and the machine vision alone were able to respectively classify 73.7% and 92.9% of the beverages correctly. When combining the electronic nose and the machine vision, the classification accuracy increased to 96.6%. Based on the results, it can be concluded that the combination of the electronic nose and machine vision is able to extract more information from the sample, hence improving the classification accuracy.**

I. INTRODUCTION

Since its emergence around 30 years ago, the electronic nose technology has been advancing tremendously. From a simple system that was capable to solve simple odor based classification problem [1], it is now equipped with sophisticated accessories and has been used to solve many problems involving odor analysis in various industries [2]. Many literatures reported the application of electronic nose in the food industry, where it was used to evaluate food freshness [3], to determine storage stability of food product [4], to determine the fruit ripeness level [5], to determine food shelf-life [6], to distinguish different types of beverages [7], to name a few. The extensive applications of electronic nose in food industry were due to the nature of food that emits unique odor which can be fairly distinguished.

Typically, the electronic nose operates as follows: detect the volatiles emitted by the food sample by using the gas sensor array, obtain the valuable information from each of the sensor response, and finally identify the food sample. To execute the above operation, the electronic nose has a gas sensor array, a data acquisition and controller system and a data analysis software. The gas sensor array consists of several chemical gas sensors with different selectivity and sensitivity. The number, type and selectivity of the sensor array are determined either using the blackboard approach [8] or by using the experimental approach [2]. On average, 3 to 8 sensors were normally used, however the number can go to 32 sensors [9]. Each sensor in the array interacts with the volatiles emitted by the food sample. The interaction produces certain changes in the sensor, usually presented by the increasing or decreasing of resistance. The resistance changes were further presented as voltage difference that can be processed by the data acquisition and controller system. The information contain in the sensor response was extracted. The combination of information obtain from every sensor response will form a pattern that represents the food sample. Based on this pattern, the data analysis software will identify the food sample.

The electronic nose alone was proven able to solve many odor based classification problems with high accuracy [10, 6]. However, efforts were made to improve the classification performance especially for difficult problems. Among the efforts are: using different sensors technology, using different features of the sensor response, and using different data analysis techniques [11]. Apart from modifying the electronic nose itself, there were attempts to combine the electronic nose with other tools such as the electronic tongue [12, 13], the mass spectrometer [14] and the machine vision [15, 16]. These combinations were performed to extract more information from the sample in order to improve discrimination between classes. However the electronic tongue requires direct contact to the sample while the mass spectrometer requires the sample to be vaporized. These requirements spoil the contents and destroy the sample physically, thus are considered destructive. The machine vision on the other hand offers the ability to extract physical information of the sample while preserving the sample.

This paper presents the classification of beverages by using the combination of electronic nose and machine vision systems. As comparison, the classification of beverages was also performed by using the electronic nose system individually and machine vision individually. The electronic nose and machine vision systems were described briefly in the following sections. The classification of beverages was executed with the help of supervised Support Vector Machine.

II. MATERIALS & METHODS

A. Beverages samples

In this study, 15 beverages from 4 different types of beverages: original flavor fresh milk, chocolate flavor fresh milk, original flavor soy milk and original flavor cultured milk were used. They constituted of 4 original flavor fresh milks from different manufacturers (AA, AB, AC, AD), 3 chocolate flavor fresh milks from different manufacturers (CA, CB, CC), 4 original flavor soy milks from different manufacturers (SA, SB, SC, SD) and 4 original flavor cultured milks from different manufacturers (KA, KB, KC, KD). The same type of beverages emanated almost identical odor and also possessed almost similar color trait and therefore were difficult to identify by using sensory analysis. A total of 228 packets of beverages were collected and 10 ml from each packet were used for odor measurement and image acquisition. These 228 beverages were distributed evenly into training and testing data sets respectively.

B. The Electronic Nose System

A MOS based electronic nose system was designed and developed at the Digital Signal Processing Laboratory, Universiti Kebangsaan Malaysia. The developed system consists of 5 parts: a sample chamber, a sensor chamber, a data acquisition system and controller unit, a power supply unit and a graphic user interface (GUI) system (7). The sample chamber is a 40ml cylindrical glass bottle. It is attached to the sensor chamber by an air diaphragm pump. There are 14 Metal Oxide Sensors (TGS822, TGS813, TGS821, TGS2602, TGS2180, TGS826, TGS2620, TGS825, TGS830, TGS6812, TGS2610, TGS2600, TGS2612 and TGS2611) and 1 temperature sensor (LM35DZ) mounted on the base of the 200 ml sensor chamber. The operation of the electronic system is controlled by the GUI system developed using the Borland C++ Builder software.

The measurement process is as follows. The ambient air is pumped in and out of the sensor chamber for 200s. This is to ensure that the sensor chamber is free from any volatiles from previous measurement hence providing a stable baseline. When the 200s cleaning period is over, the sample chamber with the beverage sample is attached to the sensor chamber and the beverage’s odor is sucked to the sensor chamber for 200s. Then the sensor chamber is clean again for another 200s. During measurement process, the voltage response of each sensor is recorded (Fig. 1). From the response, the degree of reaction of each sensor given by eq. 1 is computed. This produces 14 variables which correspond to 14 gas sensors. However only 10 variables obtained from TGS822, TGS813, TGS821, TGS2602, TGS826, TGS2620, TGS825, TGS830, TGS2610 and TGS2600 sensors were used since they produce significant response to the beverage samples. The combination of these variables is considered as the odor feature of the measured beverage.

$$r = (V_{max} - V_{min})/V_{min} \tag{1}$$

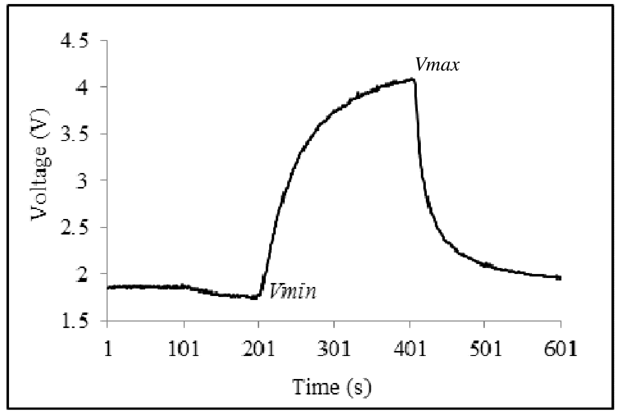

Fig. 1 The voltage response curve of TGS822 sensor.

C. The Machine Vision System

A machine vision system was developed in the Digital Signal Processing Laboratory, Universiti Kebangsaan Malaysia. The system consists of Lumenera USB Camera (LU100C) with 1280 x 1024 resolution and focal length of 4 to 8 mm. The lens has been set to cover a scene area of approximately 8 cm x 8 cm with the distance between lens and sample approximately 10 cm. A light box of 20 cm (height) x 9 cm (width) x 9 cm (depth) with white Light Emitting Diode (LED) has been constructed to provide uniform illumination to the captured image. The light box is constructed from a black perspex glass and the inner side of the box was coated with black paper to reduce glare and specular reflection. The camera is controlled using a program written in Borland C++ Builder. The program is able to preview, capture and save the captured image in 24 bit RGB color space.

A portion of the image (145 x 145 pixels) is used for color evaluation. The Red, Green and Blue components of the image portion were extracted and transformed to normalized RGB (nRGB) color space [17]. The nRGB color space removes the brightness and shadow caused by light i.e removes the effect of any intensity variations in the RGB image. The nRGB can be obtained as follows:

$$n_r = R/(R+G+B) \tag{2}$$

$$n_g = G/(R+G+B) \tag{3}$$

$$n_b = B/(R+G+B) \tag{4}$$

The 3-components of nRBG color space are discretized to 3 histograms with 100 bins each. From each histogram, 2 parameters are recorded. The parameters are the maximum value and the bin of the maximum value occurs in the histogram. The combination of the maximum values and its corresponding bins obtained from the color space were regarded as the color feature of the measured beverage.

D. *Classification*

The classification is achieved by using Support Vector Machine (SVM). The SVM is a learning algorithm that receives a lot of attention lately and used to solve many classification problems. It is a trainable machine which predicts the output from the given input. The SVM has been established on the unique structural risk minimization principle which seeks to minimize an upper bound of generalization error, consists of the sum of training error and confidence interval. This feature contributes to higher generalization ability of SVM compared with other machine learning algorithms [18-19]. The training of SVM is equivalent to solving a linear constrained quadratic programming problem which make the solution of SVM is always unique and globally optimal. To solve the SVM problem, the optimization algorithms such as Interior Point Algorithms [20] and Sequential Minimal Optimization can be used [21].

SVM was originally developed to solve linear binary classification problem. The idea is to create a hyperplane that separates the classes in such a way that the margin of the classes is maximized. However for classes that are not linearly separable, SVM uses kernel function to transform the original data into higher dimensional space. SVM is also capable to solve multi-classification problem by employing one-against-all, one-against-one and pairwise methods [22].

In this paper, the Linear kernel, 3rd degree Polynomial kernel, Gaussian kernel and Sigmoid kernel were used. The value of C was assigned to 500, and the value of γ in the Gaussian and Sigmoid functions was set to 0.05 and 0.5 respectively (23). The odor feature and the color feature were auto scaled before being fed to the SVM. The auto scaling was performed using (5), where μ and σ are the mean and standard deviation of the data, respectively.

$$d_i = (d_i - \mu)/\sigma \tag{5}$$

III. RESULTS AND DISCUSSIONS

Fig. 2 displays the odor feature and color feature for the 15 beverages. Number 1 to 10 in the odor feature represent TGS822, TGS813, TGS821, TGS2602, TGS826, TGS2620, TGS825, TGS830, TGS2610 and TGS2600 while number 1 to 6 in the color feature represent the maximum value and its corresponding bin for nR, nG and nB histograms. From the figure, it can be observed that the odor features for the same type of beverages exhibit slight different pattern among themselves and exhibit noticeable dissimilar pattern between different beverage types. The original flavor fresh milks emanate the weakest odor among them, followed by chocolate flavor fresh milks, original flavor soy milks and original flavor cultured milks. Different observation is noted from the color features of 15 beverages given in Fig. 2. It is observed that the color features of the beverages contain noticeable different patterns among themselves even for beverages of the same type. This may be contributed by the amount of coloring substance introduced to the beverage by the manufacturers.

TABLE I
THE CLASSIFICATION ACCURACY FOR 15 BEVERAGES

Kernel	Odor feature	Color feature	Odor-color feature
Linear	72.8%	93.0%	96.6%
Polynomial	73.7%	86.3%	95.7%
Gaussian	65.8%	80.7%	92.2%
Sigmoid	21.9%	53.5%	42.2%

Table 1 shows the classification performance of SVM using odor feature, color feature and odor-color feature as inputs. The best classification performance using odor feature (73.7%) was obtained by using the Polynomial SVM. For the color feature and the odor-color feature, the Linear SVM produces the best classification performance with 93.0% and 96.6% accuracy, respectively. Table 2 shows the confusion matrix for the best classification accuracy obtained. The table shows that by using odor feature, the Polynomial SVM is able to classify 3 original flavor soy milks (SB, SC and SD) and all 4 cultured milk drinks (KA, KB, KC and KD) perfectly. The other beverages are correctly classified around 40% to 70%. Further observation shows that the misclassified original flavor fresh milk is classified as chocolate flavor fresh milks and the misclassified chocolate flavor fresh milk is classified as original flavor fresh milk, while the misclassified SA were classified as SD. Therefore it can be concluded that by using odor feature alone, the Polynomial SVM is able to discriminate the beverages into 3 classes i.e. fresh milks, soy milks and cultured milks.

With Linear SVM, by using color print is able to completely classify 14 beverages (OA, OB, OC, OD, CA, CB, CC, SB, SC, SD, KA, KB, KC and KD) to their respective classes. However this combination fails to recognize 70% of SA, which are classified as SD. Almost similar performance is obtained by Linear SVM by using odor-color feature as input. The Linear SVM is able to classify the same 14 beverages into their classes perfectly. Apart from that, the misclassification of SA is also reduced to 40%. This proves that the use of odor-color feature improves the classification performance.

IV. CONCLUSION

The classification of 15 beverages by using the electronic nose only, the machine vision only and the combination of electronic nose and machine vision were presented in this paper. The results showed that the classification based on the electronic nose alone produced the lowest accuracy while good classification accuracy was obtained by using machine vision alone. By combining the electronic nosed and machine vision, the classification performance was improved. To conclude, this study shows that the electronic nose and machine vision combination has the potential as a new analytical tool that is not destructive, easy to handle and also cost effective. The new tool benefits in quality assessment or quality control of beverages, fruit grading and in shelf life evaluation of food products.

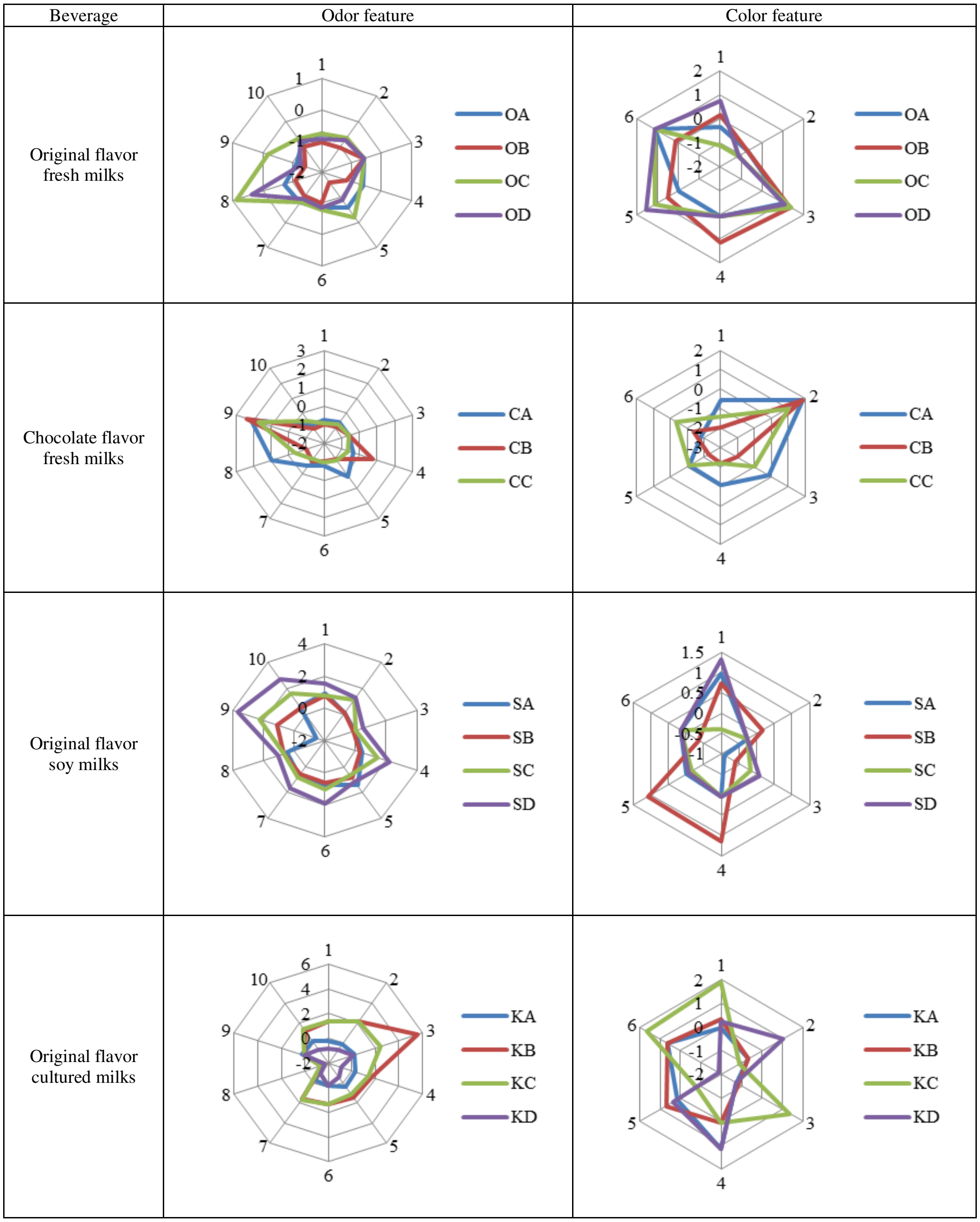

Fig. 2 The odor print and color print of 15 beverages.

TABLE 2
CONFUSION MATRIX FOR THE BEST CLASSIFICATION ACCURACY

Type	Actual	Feature	Predicted															Classification accuracy (%)	
			OA	**OB**	**OC**	**OD**	**CA**	**CB**	**CC**	**SA**	**SB**	**SC**	**SD**	**KA**	**KB**	**KC**	**KD**	**15 beverages**	**4 different types**
Original flavor fresh milks	OA	Odor	**4**	3				3										40.0	
		Color	**10**															100.0	
		Odor-Color	**10**															100.0	
	OB	Odor	1	**7**				2										70.0	70.0
		Color		**10**														100.0	100.0
		Odor-Color		**10**														100.0	100.0
	OC	Odor			**3**		2											60.0	
		Color			**5**													100.0	
		Odor-Color			**5**													100.0	
	OD	Odor		1		**2**		1	1									40.0	
		Color				**5**												100.0	
		Odor-Color				**5**												100.0	
Chocolate flavor fresh milks	CA	Odor			5	1	**4**											40.0	
		Color					**10**											100.0	
		Odor-Color					**10**											100.0	
	CB	Odor	3					**7**										70.0	56.0
		Color						**10**										100.0	100.0
		Odor-Color						**10**										100.0	100.0
	CC	Odor	1			1			**3**									60.0	
		Color							**5**									100.0	
		Odor-Color							**5**									100.0	
Original flavor soy milks	SA	Odor								**5**	5							50.0	
		Color								**3**			7					30.0	
		Odor-Color								**6**			4					60.0	
	SB	Odor								2	**10**							100.0	100.0
		Color									**10**							100.0	100.0
		Odor-Color									**10**							100.0	100.0
	SC	Odor										**10**						100.0	
		Color										**10**						100.0	
		Odor-Color										**10**						100.0	
	SD	Odor										2	**10**					100.0	
		Color											**10**					100.0	
		Odor-Color											**10**					100.0	
Original flavor cultured milks	KA	Odor												**5**				100.0	
		Color												**5**				100.0	
		Odor-Color												**5**				100.0	
	KB	Odor													**5**			100.0	100.0
		Color													**5**			100.0	100.0
		Odor-Color													**5**			100.0	100.0
	KC	Odor														**5**		100.0	
		Color														**5**		100.0	
		Odor-Color														**5**		100.0	
	KD	Odor															**5**	100.0	
		Color															**4**	100.0	
		Odor-Color															**4**	100.0	

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