COMPUTER VISION CLASSIFICATION OF POTATO CHIPS BY COLOR

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ABSTRACT

In this research the automatic classification of commercial potato chips by computer vision was studied. The general objective was to design a tool that would be able to classify objectively potato chips according to their color in different categories. For this purpose, sensory measurements of color in 100 potato chips were correlated with the corresponding objective measurements obtained by computer vision system. Potato chips with and without ruffles of different brands were used for training and validation experiments. Sensory evaluations were done with a special chart that classifies potato chips in seven color categories. Simultaneously, the color of the same potato chips classified by the sensory panel, was determined objectively by a computer vision system in L*, a*, b* *units. A linear regression model was good enough to predict potato chip sensory color values from the corresponding instrumental measurements by computer vision. The linear model after following the process of crossed validation crossed presented an error of ~4% for smooth chips (without ruffles) and ~7% for chips with ruffles.*

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PRACTICAL APPLICATIONS

The automatic classification methodology presented for potato chips is general and has a wide range of potential uses. It could be applied not only to other potato cultivars and frying conditions but also to other less heterogeneous raw materials and unit operations different than potato and frying, respectively. The computer vision system used in this research could as well be very useful in the food industry as a large amount of information can now be obtained from measurements at the pixel level that allows a better characterization of foods and thus improves quality control.

INTRODUCTION

In the potato chip industry, each batch of potato tubers must be tested for quality before processing, and visual aspect is, of course, of great importance (Marique *et al.* 2003). Some research groups are working on new automated ways to evaluate potato tuber quality in order to determine whether they are suitable for processing (i.e., surface appearance, illness, shape, bruises, etc.). This is strongly linked to image feature extraction, which is one of the most active research topics in computer vision (CV). Some studies related to machine vision inspection of raw potatoes have been reported in the literature. For instance, automated inspection stations for machine vision grading of potatoes in size and shape have been reported; however, these systems cannot fulfill the potato industry requirements for high throughput and real-time speed (Tao *et al.* 1990; Deck *et al.* 1992; Grenander and Manbeck 1993; Heinemann *et al.* 1996).

In 2001 about 50% of the U.S. potato crop was processed to produce 11,300 million kg of processed potatoes, of which 21.6% was made into chips. Consumption of potato chips in the U.S.A. has increased from 11.4 lbs per person in 1960 to 19.3 lbs in 2007. About 38% of all households consuming potato chips are located in the southern United States (Economic Research Service [ERS] of the United States Department of Agriculture 2008). Potato chips are thin slices whose moisture content decreases from around 80% to almost 2% when they are fried. However, the frying process inevitably leads to a considerable oil uptake of around 35%, which is mostly located on the chip surface (almost no penetration during frying) and adhered to the piece surface at the end of the frying process (Pedreschi *et al.* 2008).

Color is considered the most important visual attribute in the perception of potato chip quality and is an extremely important criterion for the potato processing industry, which is strictly related to consumer perception (Scanlon *et al.* 1994; Segnini *et al.* 1999; Pedreschi *et al.* 2006; Mendoza *et al.* 2007). Color development only begins in potato chips when sufficient amount of drying has occurred and depends also on the drying rate and the heat-transfer coefficients during the different stages of frying (Pedreschi *et al.* 2006). Potato chip color is the result of Maillard reaction that depends on the content of reducing sugars, amino acids or proteins at the surface. It is also affected by the frying temperature and time (Márquez and Añón 1986). Although there are different color spaces, the most commonly used in the color measuring of foods is the L^*, a^*, b^* color space because of the uniform distribution of colors, and because it is very close to human perception of color (León *et al.* 2006). It is worth to mention that acrylamide, a chemical compound that is formed in potatoes during frying and is highly related to the color of potato chips, has recently been found to be critical for human health as it is a carcinogenic agent in rats (Mottram and Wedzicha 2002; Rosen and Hellenäs 2002; Stadler *et al.* 2002; Pedreschi *et al.* 2005).

Rapid advances in hardware and software for digital processing have motivated several studies on the development of CV systems to evaluate the quality of diverse raw and processed foods (Gunasekaran and Ding 1994; Brosnan and Sun 2003). Visual aspects such as surface color and appearance can be studied using CV techniques in order to determine the potato chip quality (Pedreschi *et al.* 2007). A general CV pattern recognition process required for the automatic classification of potato chips involves the following four steps (Castleman 1996; Pedreschi *et al.* 2004): image acquisition; image preprocessing and segmentation; feature extraction; and classification. Several CV techniques have been reported in order to assess the quality of fried potatoes (Pedreschi *et al.* 2007). In European factories, some CV systems are used for the on-line evaluation of potato chips, allowing chips to be sorted according to defects like black spots or blisters (Marique *et al.* 2005). Pedreschi *et al.* (2006) designed and implemented an inexpensive CV system for measuring the color of highly heterogeneous food material, not only in shape as well as in color, such as potato chips. Additionally, León *et al.* (2006) calibrated a CV system to carry out image color transformation in RGB units to L^*, a^*, b^* units by finding a proper model and estimating its parameters. Mendoza *et al.* (2007) evaluated the suitability of using color and textural features to characterize and classify commercial potato chips in four quality categories according to their appearance. They found that image texture features were better that color features to discriminate both quality appearance categories and consumer preferences. Some researchers have been also working on a promising device that is able both to classify chips according to color and to predict acrylamide levels using neural networks (Marique *et al.* 2003, 2005). Marique *et al.* (2003) used a pattern recognition methodology to classify fried potato chips with an artificial neuronal network (ANN) and multiple linear regression (MLR) reporting a good agreement with the human inspectors, yielding a classification performance in the validation data of almost 90 and 88 % for ANN and MLR, respectively. Apart from the neural network, there is another device based on statistical pattern recognition for color classification of potato chips (Marique *et al.* 2003; Pedreschi *et al.* 2004). Pedreschi *et al.* (2004) used pattern recognition from pixel information contained in two-dimensional images to study the visual properties of potato chips and to classify them according to their processing conditions. The general objective of this research was to design a CV tool that would be able to classify potato chips fast, objectively and accurately according to their color in categories.

MATERIALS AND METHODS

Materials

Smooth and undulated (with ruffles) commercial potato chips of different brands bought in a Chilean supermarket were used in the experiments (see Fig. 1). For experiments with smooth chips, a sample composed of one hundred chips coming from four packages of different commercial brands was tested. In the case of undulated chips, the analyzed sample was composed of one hundred chips coming from two packages of different commercial brands.

Color Determination by Sensory Analysis

Sensory color analysis of potato chips was accomplished by a panel formed by eleven assessors previously selected according to their ability to

FIG. 1. SAMPLES IN THE UPPER AND LOWER PART OF THE FIGURE CORRESPOND TO SMOOTH AND UNDULATED POTATO CHIPS USED IN OUR EXPERIMENTS, RESPECTIVELY
Potato chips from right to left in the figure tend to get darker.

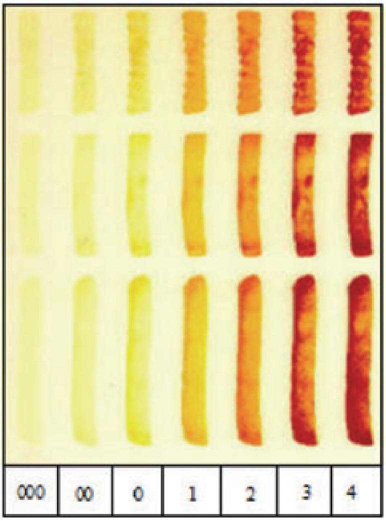

FIG. 2. CHART FOR SENSORY ANALYSIS OF COMMERCIAL POTATO CHIP COLOR (BELGAPOM, BRUSSELS, BELGIUM)

discriminate different color intensities. Fourteen subjects without previous sensory training were recruited among students (age range of 20–26 years) of the Universidad de Santiago de Chile. The assessors were selected according to their ability to rank the intensity of two series of color dilutions of tartrazine (0.010%) and sunset yellow (0.015%), consisting of 10 test tubes each in concentrations of 100, 90, 80, 75, 70, 65, 60, 55, 50 and 45% diluted with water, given in random order. A minimum of 60% correct responses were established as selection criterion, as previous assays carried out by the authors showed that below this limit there exists limited sensory acuity or even impairment of color vision. No further selection or training was performed until the test procedure, in which each assessor classified the color of each of the one hundred selected potato chips by using the standard color chart (Belgapom, Brussels, Belgium) presented in Fig. 2. This chart was designed to evaluate the color of French fries, but it has been used successfully as well to evaluate the color of potato chips (Marique *et al.* 2005).

Numbers from 0 to 6 were assigned to each different fried potato color category (from 000 to 4), as can be seen in Table 1, in order to calculate the sensory color index (SCI).

The eleven sensory assessors visually classified the color of each selected chip. The SCI of each chip was calculated, defined as:

TABLE 1.
NUMBERS ASSIGNED TO EACH COLOR CATEGORY OF THE COLOR CHART SHOWED IN FIG. 2

Color category	000	00	0	1	2	3	4
Number	0	1	2	3	4	5	6

$$SCI = \frac{\sum_{i=0}^{6} i \times n_i}{\sum_{i=0}^{6} n_i} \qquad (1)$$

where n_i is the number of assessors that classified the chip in color category i. The total number of assessors $\sum_{i=0}^{6} n_i$ was 11. One hundred potato chips were analyzed in both the undulated and smooth potato chip experiments.

Color Measurement by CV System (CVS)

For quantifying fast, accurately and objectively the color of commercial potato chips, a CVS implemented by Pedreschi *et al.* (2006) was used. This CVS is composed by routines in MATLAB specially developed to segment the potato chips images (Mery and Pedreschi 2005) and to convert RGB images into L^*, a^*, b^* units (León *et al.* 2006), as shown in Fig. 3.

First, images were captured using an image acquisition system for color digital camera (CDC) where samples were illuminated using four fluorescent lamps (length of 60 cm) with a color temperature of 6,500°K (Philips, Natural Daylight, 18 W, Philips, Ontario, Canada) and a color rendering index (Ra) close to 95%. The four lamps were arranged as a square 35 cm above the sample and at an angle of 45° with the sample plane to give a uniform light intensity over the food sample. A CDC Power Shot G3 (Canon, Tokyo, Japan) was located vertically at a distance of 22.5 cm from the sample. The angle between the camera lens axis and the lighting sources was around 45°. Sample illuminators and the CDC were inside a wood box whose internal walls were painted black to avoid the light and reflection from the room. The white balance of the camera was set using a standardized gray color chart from Kodak (Boston, MA). Color standards were photographed and analyzed periodically to ensure that the lighting system and the CDC were working properly.

Images were captured with the mentioned CDC at its maximum resolution (2,272 × 1,704 pixels) and connected to the USB port of a Pentium IV,

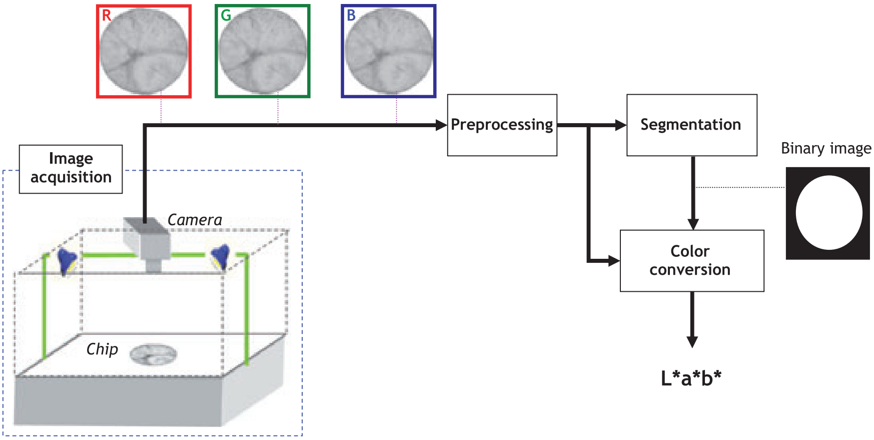

FIG. 3. SCHEMATIC REPRESENTATION OF THE COMPUTER VISION SYSTEM IMPLEMENTED FOR OBJECTIVE COLOR MEASUREMENT IN L^*, a^*, b^* UNITS POTATO CHIPS

1,200-MHz computer. Canon Remote Capture Software (version 2.7.0, Intel, Santa Clara, CA) was used for acquiring the images directly in the computer in TIFF format without compression. The digital images were preprocessed to improve their quality before they are analyzed. Using digital filtering the noise of the image can be removed and the contrast can be enhanced. In addition, in this step the color image is converted to a grayscale image, called the intensity image [I]. In order to reduce the computational time of processing the images were sub-sampled to $1{,}136 \times 852$ pixels. A linear Gaussian low pass filter (Castleman 1996) was applied in order to reduce the noise in the images.

Then, the intensity image was used to identify disjoint regions of the image with the purpose of separating the part of interest from the background. This segmented image [S] is a binary image consisting only of black and white pixels, where "0" (black) and "1" (white) mean background and object, respectively. Image segmentation (to separate the true image of the potato chips from the background) was performed using a threshold combined with an edge detection technique based on the Laplacian-of-Gaussian filter (Castleman 1996). In our case, the region of interest within the image corresponds to the area where the potato chip is located and a robust algorithm for proper potato image segmentation was previously developed and implemented (Mery and Pedreschi 2005). Finally, conversion of RGB images into L^*, a^*, b^* units was accomplished according to León and *et al.* (2006).

Models for Automatic Classification of Color

In this section, we explain in further details the models that are able to predict the responses of the sensor panel. The attempt is made to determine automatically from the L^*, a^*, b^* measurements of a sample, the same color that would give the sensory analysis by seeing the sample. Additionally, we show how to estimate the parameters of the models. Finally, we calculate the error of the prediction using cross-validation.

We define the variable y as the SCI value obtained by the sensory panel (see Eq. 1), and $\hat{y}$ as the estimated value for y obtained by a linear model:

$$\hat{y} = a_0 + a_1 x_1 + a_2 x_2 + a_3 x_3 \tag{2}$$

or a quadratic model:

$$\hat{y} = a_0 + a_1 x_1 + a_2 x_2 + a_3 x_3 + a_4 x_1 x_2 + a_5 x_1 x_3 + a_6 x_2 x_3 + a_7 x_1^2 + a_8 x_2^2 + a_9 x_3^2 \tag{3}$$

where x_1, x_2, x_3 are the values L^*, a^*, b^*, respectively, obtained by the CVS, and $a_0 \ldots a_m$ are the parameters of the model ($m = 3$ for linear model and $m = 9$ for quadratic model). Vector parameter $\hat{\mathbf{a}} = [a_0 \ldots a_m]^T$ can be easily estimated using a linear regression approach (see for example Ljung 1999). Usually, the error of the estimation is calculated as:

$$e = \frac{1}{n} \sum_{i=1}^{n} |y_k - \hat{y}_i| \tag{4}$$

However, the error can be estimated in a better way using cross-validation, a technique widely used in machine learning problems (Mitchell 1997). In cross-validation, the data is divided into v groups. Each group contains N/v samples, where N is the total number of samples of the data. The parameters of the model are estimated using the 'estimation data' defined as the data of v-1 groups, whereas the error of the model is computed using Eq. (4) for the 'testing data' defined as the data of the group that was not included in the mentioned v-1 groups. Thus, one can evaluate how well the model works with samples that have not already used to estimate the parameters of the model. This process is repeated v times. In each test, the testing data corresponds to a different group, and the error obtained in each experiment is called e_k, for $k = 1, \ldots, v$. In our experiments we use $v = 10$ as shown in Fig. 4. The average of the v calculated errors correspond to the estimation of the error of the model:

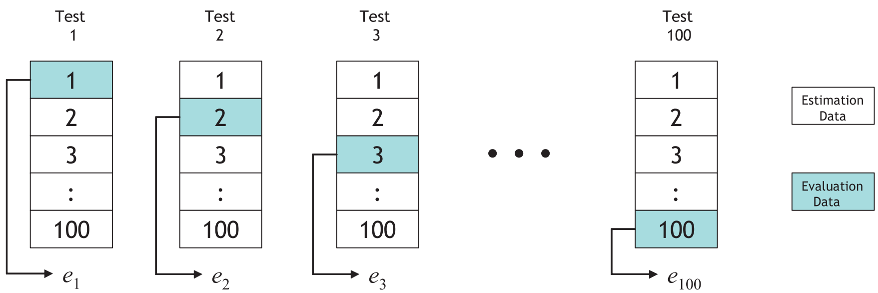

FIG. 4. SCHEMATIC REPRESENTATION OF THE CROSS-VALIDATION WITH PROCEDURE TO VALIDATE THE MODELS

$$e_{\mathrm{T}} = \frac{1}{v}\sum_{k=1}^{v} e_k \tag{5}$$

We calculate the normalized error as

$$\bar{e} = \frac{e_{\mathrm{T}}}{y_{\max}} \tag{6}$$

where $y_{\max}$ is the maximal value in the scale of y. According to Table 1, $y_{\max} = 6$. Thus, $\bar{e}$ gives values between 0 and 1. In this case, 0 means that there is no error between model and sensor panel, and 1 means that there is an error of 100%.

Additionally, we estimate: (1) R, the correlation coefficient between y and $\hat{y}$; (2) the lower confidence bound and upper confidence bound of the estimated error for 95% confidence; (3) the lower confidence bound and upper confidence bound of the estimated parameters for 95% confidence; and (4) the P value (calculated as the probability to obtain a correlation as large as the observed value by a random variable, when the true correlation is zero) (Mathworks Inc. 2009).

RESULTS AND DISCUSSION

Sensory classification of potato chip color was accomplished successfully using the SCI by the sensory panel, composed by the 11 assessors previously selected according to their ability to rank correctly different color intensities. On the other hand, the CVS used in this research consisted of two parts: (1) the image acquisition set up as shown in Fig. 3; and (2) the digital image analysis part composed of a set of routines to preprocess the acquired and stored images, to segment the images and to separate objects of interest from the background, and to convert RGB images of the objects of interest into L^*, a^*, b^* units of color. In this research the digital image analysis routines were programmed in MATLAB as explained in (León *et al.* 2006; Pedreschi *et al.* 2006). As shown in Fig. 5, once potato chips were analyzed by both sensory classification and CV, regression procedures (either linear or quadratic) were established to determine the correlation between the SCI values and the L^*, a^*, b^* values. Finally, the cross-validation procedure was accomplished in order to evaluate the performance of the models.

Two models were built that were able to estimate SCI accurately in smooth potato chips and with less accuracy in potato chips with ruffles. The best results were achieved with the quadratic model, which showed smaller errors but not considerable than the linear model (Tables 2 and 3). In all of our experiments, the P value is zero; this means that the correlation R is significant. Figure 6 shows the graphs of real and estimated values for the linear and quadratic models for smooth and undulated potato chips, and there is evidently a great deal of similarity between the estimated values using the models and

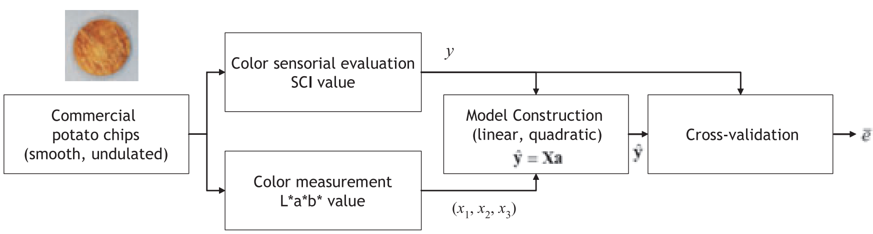

FIG. 5. SCHEMATIC DIAGRAM OF THE PROCESS FOLLOWED TO CLASSIFY AUTOMATICALLY POTATO CHIPS USING COMPUTER VISION
SCI, sensory color index.

TABLE 2.
CORRELATION AND ERROR IN ESTIMATED SENSORY COLOR INDEX IN SMOOTH AND UNDULATED POTATO CHIPS

Set	Model	R	$\bar{e}$ with 95% confidence
Smooth	Linear	0.9711	$0.0249 < \bar{e} = 0.386 < 0.0524$
	Quadratic	0.9790	$0.0226 < \bar{e} = 0.361 < 0.0496$
Undulated	Linear	0.7869	$0.0490 < \bar{e} = 0.649 < 0.0808$
	Quadratic	0.8245	$0.0451 < \bar{e} = 0.609 < 0.0766$

TABLE 3.
ESTIMATED PARAMETERS (EST) FOR EACH MODEL INDICATING, LOWER CONFIDENCE BOUND (LOW) AND UPPER CONFIDENCE BOUND (UP) FOR 95% CONFIDENCE

Set	Model		a_0	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9
Smooth	Linear	est	4.05	–0.044	0.049	0.098	–	–	–	–	–	–
		low	1.94	–0.07	0.0098	0.089	–	–	–	–	–	–
		up	6.17	–0.015	0.088	0.11	–	–	–	–	–	–
	Quadratic	est	32.28	–0.91	–1.99	0.53	0.0066	0.029	–0.0031	0.0306	–0.0050	–0.0069
		low	–7.78	–1.99	–3.13	0.22	–0.0007	0.0097	–0.0049	0.0142	–0.0091	–0.0190
		up	72.35	0.17	–0.89	0.85	0.014	0.048	–0.0014	0.0471	–0.0009	0.0052
Undulated	Linear	est	5.24	–0.059	0.035	0.077	–	–	–	–	–	–
		low	1.31	–0.11	–0.031	0.052	–	–	–	–	–	–
		up	9.16	–0.009	0.100	0.102	–	–	–	–	–	–
	Quadratic	est	71.77	–1.75	–2.85	–0.35	0.0104	0.0135	–0.0045	0.0288	0.0082	0.0333
		low	–17.88	–3.74	–5.31	–2.06	–0.0006	–0.022	–0.0094	–0.0027	–0.0131	0.0044
		up	161.4	0.24	–0.39	1.36	0.0214	0.0494	0.0003	0.0604	0.0295	0.0621

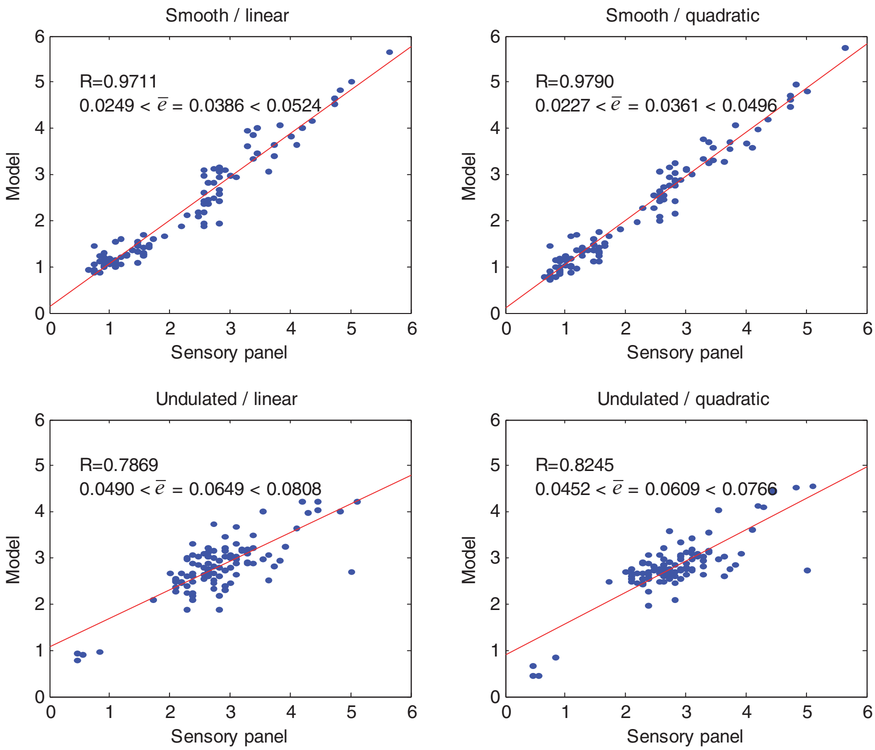

FIG. 6. ESTIMATION OF SENSORY COLOR INDEX VALUES FOR LINEAR AND QUADRATIC MODEL IN SMOOTH AND UNDULATED POTATO CHIPS

the real values for smooth potato chips yielding correlation coefficients. For undulated potato chips, correlation coefficients *R* were around 0.8. Lower correlation between objective and sensorial measurements of color in potato chips with ruffles could be caused by the higher complexity of their surfaces because of the presence of undulated patterns that has a pronounced effect in the way that consumers perceive the color. This effect is not perceived with smooth potato chips as these undulated patterns are not present.

In this research simple models (linear and quadratic) are presented, which efficiently predict the SCI of potato chips, especially when they are smooth (without ruffles). These results are in agreement with those found by Marique *et al.* (2003) using more complex techniques such as pattern recognition methodology to classify potato chips with an artificial neural network and MLR. These authors reported a good agreement with sensory assessors yielding classification performance in the validation data of almost 90% in both cases. The methodology presented in this article is general and has the ability to be applied in the fried potato industry in order to replace human operator classification by an automatic classification. Also, the selection process of the sensory panel was accomplished by a very simple procedure achieving a good panel performance.

CONCLUSIONS

Eleven sensory panelists were successfully chosen by a simple selection process in order to perform sensory color classification. Color measured by the sensory assessors was highly correlated with the color determined objective in L^*, a^*, b^* units by a CV system. Two models were built in order to predict accurately the SCI and to classify commercial potato chips (undulated and smooth) in seven color categories. Linear and quadratic models showed small errors in smooth potato chips (close to 4%).

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