Classification of Potato Chips Using Pattern Recognition

F. PEDRESCHI, D. MERY, F. MENDOZA, AND J.M. AGUILERA

ABSTRACT: An approach to classify potato chips using pattern recognition from color digital images consists of 5 steps: (1) image acquisition, (2) preprocessing, (3) segmentation, (4) feature extraction, and (5) classification. Ten chips prepared for each of the following 6 conditions were examined: 2 pretreatments (blanched and unblanched) at 3 temperatures (120 °C, 150 °C, and 180 °C). More than 1500 features were extracted from each of the 60 images. Finally, 11 features were selected according to their classification attributes. Seven different classification cases (for example, classification of the 6 classes or distinction between blanched and unblanched samples) were analyzed using the selected features. Although samples were highly heterogeneous, using a simple classifier and a small number of features, it was possible to obtain a good performance value in all cases: classification of the 6 classes was in the confidence interval between 78% and 89% with a probability of 95%.

Keywords: potato chips, color, image analysis, classification, pattern recognition, image texture, feature extraction

Introduction

Potatoes (*Solanum tuberosum*), one of the world's major crops, is consumed daily by millions of people from diverse cultural backgrounds. Potato chips have been a popular snack for 150 y, and their retail sales in the United States (about \$6 billion/y) represent 33% of the total sales of snacks in the U.S. market (Garayo and Moreira 2002; Clark 2003). The consumer's attraction to potato chips is largely because of major changes in their microstructure induced by frying and their effects on physical and sensorial properties (Pedreschi and Aguilera 2002). Color of potato chips is an important parameter to be controlled during processing together with crispness and oil content (Smith 1975; Scanlon and others 1994). Color is the result of the Maillard reaction, which depends on the content of reducing sugars and amino acids or proteins at the surface and the temperature and time of frying (Márquez and Añón 1986).

In defining and quantifying color, a color system must be selected, usually among 4 alternatives: $L^*a^*b^*$, RGB (red, green, blue), XYZ, and CMYK (cyan, magenta, yellow, black). $L^*a^*b^*$ is an international standard for color measurements, adopted by the Commission Internationale d'Eclairage (CIE) in 1976. This color model creates a consistent color, regardless of the device used to generate the image (for example, monitor, printer, or scanner). L^* is the luminance or lightness component, which ranges from 0 to 100, and parameters a^* (from green to red) and b^* (from blue to yellow) are the 2 chromatic components, which range from –120 to 120 (Papadakis and others 2000). In contrast with other color models, such as RGB and XYZ, in the $L^*a^*b^*$ space the color perception is uniform. This means that the Euclidean distance between 2 colors corresponds approximately to the color difference perceived by the human eye (Hunt 1991).

Computer vision (CV) is a technology for acquiring and analyzing an image of a real scene by computers to obtain information or to control processes (Brosnan and Sun 2003). CV has been used in the food industry for quality evaluation; detection of defects; and identification, grading, and sorting of fruits and vegetables, meat and fish, bakery products, and prepared goods, among others (Gunasekaram and Ding 1994; Gerrard and others 1996; Luzuriaga and others 1997; Leemans and others 1998; Sun 2000; Shanin and Symons 2001; Shanin and Symons 2003). In particular, CV has been used to objectively measure the color of fried potatoes by mean of gray-level values (Scanlon and others 1994). A computer-based video system was developed to quantify the color of potato chips in the $L^*a^*b^*$ color space, which correlated well with the perception of the human eye (Segnini and others 1999). The video image analysis technique had some obvious advantages over a conventional colorimeter, namely, the possibility of analyzing the whole surface of the chips and quantifying characteristics such as brown spots and other defects.

The texture of an image is characterized by the spatial distribution of gray levels in a neighborhood. Image texture (IT) is defined as repeating patterns of local variations in image intensity that are too fine to be distinguished as separate objects at the observed resolution, that is, the local variation of brightness from 1 pixel to the next (or within a small region). IT is an important tool used in pattern recognition to characterize the arrangement of basic constituents of a material on a surface (Haralick and others 1973). IT can be used to describe such image properties as smoothness, coarseness, and regularity. Three approaches may be taken to determine features of the IT: statistical, structural, and spectral (Gunasekaram 1996). The IT of some food surfaces has been described quantitatively by fractal methods (Peleg 1993; Quevedo and others 2002). Besides fractal properties other important characteristics could be obtained from the information of an image such as statistical, geometrical, and signal-processing properties, among others.

Generally, the automatic pattern recognition process, as shown

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in Figure 1, consists of 5 steps (Castleman 1996; Mery and others 2003). The general methodology that will be applied to identify quality classes in potato chips is briefly described:

1. Image acquisition. A digital image of the object is captured and stored in the computer. When acquiring images, it is important to consider the effect of illumination intensity and the specimen's orientation relative to the illumination source because the gray level of the pixels is determined not only by the physical features of the surface but also by these 2 parameters (Peleg 1993; Chantler 1995). Typically, a color digital camera provides 3 digital images, namely, red (R), green (G), and blue (B) digital images.

2. Image preprocessing. The digital images must be 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).

3. Image segmentation. The intensity image is 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. In our case, the region of interest within the image corresponds to the area where the potato chip is located.

4. Feature extraction. Segmentation detects regions of interest inside the image or structural features of the object. Subsequently, feature extraction is concentrated principally around the measurement of geometric properties (perimeter, form factors, Fourier descriptors, invariant moments, and so forth) and on the intensity and color characteristics of regions (mean value, gradient, 2nd derivative, IT features, and so forth). The geometric features are computed from the segmented image (S), the intensity features are extracted from the intensity image (I) and the color features from the RGB images. It is important to know ahead which features provide relevant information for the classification to be accomplished. For this reason, a feature selection must be performed in a training phase.

5. Classification. The extracted features of each region are analyzed and assigned to one of the defined classes, which represent all possible types of regions expected in the image. A classifier is designed following a supervised training, and simple classifiers may be implemented by comparing measured features with threshold values. Nonetheless, it is also possible to use more sophisticated classification techniques such as those that carry out statistical and geometric analyses of the vector space of the features or those that use neural networks or fuzzy logic (Castleman 1996; Jain and others 2000; Mery and others 2003).

Marique and others (2003), for example, used a pattern recognition methodology to classify fried potato chips with an artificial neuronal network (ANN) and multiple linear regression (MLR). In this approach, 20 samples of 12 different mealy potato cultivars were analyzed. Color images of each 20 samples were acquired and converted to 8-bit gray images. Using a commercial software package, 3 mean values from 26 pixels each were computed per chip, corresponding to the apex, the center, and the basal part of the sticks, respectively. The data was divided into 2 sets: 2/3 of the data was used for the training of the classifier and the remaining 1/3 for the validation. Two classifiers (ANN and MLR) were trained to assign each chip to 1 of the 4 quality color classes established by a human jury. The authors report a good agreement with human inspectors, yielding a classification performance in the validation data of 89.9% and 87.8% for ANN and MLR, respectively.

The objective of this work was to use pattern recognition from pixel information contained in 2D images to study the visual properties of potato chips (blanched and unblanched) fried at 3 different temperatures: 120 °C, 150 °C, and 180 °C. Data will further be used to classify highly heterogeneous materials such as fried potato chips processed under different conditions.

Materials and Methods

Materials

Potatoes (variety Panda) provided by Moms (Santiago, Chile) stored at 8 °C and 95% relative humidity and sunflower oil (Chef, COPRONA, Santiago, Chile) were the raw materials. Unblanched (u) or blanched (b) slices (2.5-cm thickness) were cut from the pith of the parenchymatous region of potato tubers using an electric slicing machine (model EAS65, Berkel, U.S.A.). A circular cutting mold was used to make circular slices with a 37-mm dia. Blanched samples were prepared by heating raw slices in 5 L of hot water at 80 °C for 3.5 min (potato-to-water ratio, about 0.005 w/w). Unblanched and blanched slices were rinsed for 5 min in distilled water to eliminate loose material adhering to the surface and blotted with paper towel to remove surface water before frying.

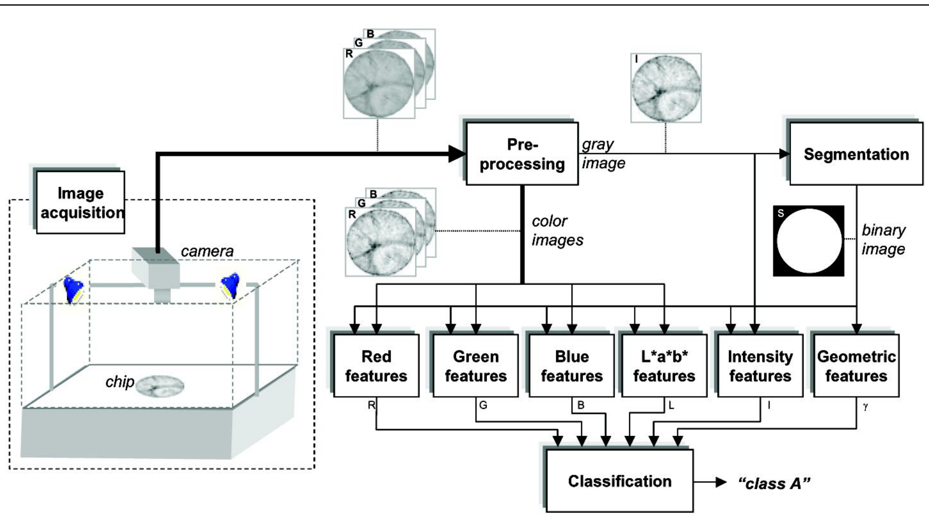

Figure 1—Schematic representation of the pattern recognition process required for the automatic classification of potato chips

Frying conditions

Ten samples of either unblanched or blanched potato slices were fried in 8 L of hot oil in an electrical fryer (Beckers, Model F1-C, Treviglio, Italy) at 3 temperatures: 120 °C, 150 °C, and 180 °C. Potato-to-oil ratio was maintained low (about 0.0035 w/w) to keep a constant temperature of frying (± 1 °C). The slices were fried at the set temperature for the minimum time (determined experimentally previously) required to reach a final moisture content of about 1.7% (wet basis). Fried chips were drained over a wire screen for 5 min to remove excess oil and then the samples were photographed.

Pattern recognition process

The pattern recognition process was performed as shown in Figure 1 using routines written in Matlab (Version 6.1, Release 12.1, Mathworks Inc., Natick, Mass., U.S.A.). A brief description of each step follows:

1. Image acquisition. Images were captured using an image acquisition system for color digital camera similar to that developed by Papadakis and others (2000), namely:

a. Samples were illuminated using 4 fluorescent lamps (60-cm length) with a color temperature of 6500 K (Philips, Natural Daylight, 18W) and a color rendering index (Ra) close to 95%. The 4 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.

b. A color digital camera (CDC) Power Shot A70 (Canon, Tokyo, Japan) was located vertically at a distance of 12.5 cm from the sample. The angle between the camera lens axis and the lighting sources was approximately 45°. Sample illuminators and the CDC were inside a wood box with internal walls that 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 (U.S.A.). Color standards were photographed and analyzed periodically to ensure that the lighting system and the CDC were working properly.

c. Images were captured with the mentioned CDC at its maximum resolution (2048 × 1536 pixels) and stored by connecting the CDC to the USB port of a PC (Pentium III, 800 MHz, 120 MB RAM, 20-GB hard disk). Canon Remote Capture Software (version 2.7.0) was used for acquiring the images directly in the computer.

2. Preprocessing. To reduce the computational time of processing, the images were subsampled to 1136 × 852 pixels. A linear Gaussian low-pass filter (Castleman 1996) was applied to reduce the noise in the images. The grayscale image was obtained using the command "rgb2gray" of Matlab. The captured digital images are shown in Figure 2.

3. Segmentation. 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; Mery and Filbert 2002). To determine actual food dimensions (geometrical parameters), a ruler was photographed under the same conditions, giving a scale factor of 106.7 pixels/cm.

4. Feature extraction. During the feature extraction process, the properties of each of the segmented regions were measured. Features extracted in this work are described in Table 1 and have been grouped into 6 types: (1) geometric (γ) (2) intensity (grayscale image) (I), (3) red component (R), (4) green component (G), (5) blue component (B), and (6) mean values of the $L^*a^*b^*$ components (L).

Geometric features provide information relative to the size and form of the segmented potato chip images. Intensity and RGB features provide information about the gray value and RGB color of the segmented regions. Features based on the RGB components were extracted with the same routines used for extraction of intensity features from the grayscale image but applied to the R, G, and B images instead. For color quantification in the $L^*a^*b^*$ space, the software Adobe Photoshop 6 (Adobe Systems Inc., San Jose, Calif., U.S.A.) was used. Only the image of the potato chip was selected from the captured picture, using the "magic wand tool" option that allows filtering the background. Once the selection was made, the histogram window of the software provided the parameter values for L^*, a^*, and b^*. For each of these 3 parameters, graphs of cumulative distribution, mean, standard deviation, and the number of the pixels for the selection were displayed. To convert L^*, a^*, and b^* values from the histogram windows to the $L^*a^*b^*$ color space, linear transformations were used (Papadakis and others 2000).

The details of how these features are calculated can be found in the references of Table 1. The total number of features extracted was 1511, namely 36 geometric features (γ), 368 intensity features (I), 368 red features (R), 368 green features (G), 368 blue features (B), and 3 $L^*a^*b^*$ features (L). The notation "$\{f\}_X$" was used to identify the feature f of the type X according to the 2nd column of Table 1. For example, $\{D\}_R$ means the mean 2nd derivative of the red image of potato chips.

To reduce computational time required in the pattern recognition process, it was necessary to select the features that were relevant for the classification. The feature selection was carried out based on the sequential forward selection (SFS) method (Jain and others 2000). This method requires an objective function f that evaluates the performance of the classification using m features. The objective function used was the well known Fisher linear discriminant (Fukunaga 1990), defined as the ratio of the between-class scatter matrix to the within-class scatter matrix. In this case, the larger the Fisher linear discriminant, the better the separability of the classes. The SFS begins with the search of the best individual feature that maximizes the function f (with $m = 1$). Subsequently, a 2nd search is carried out for that feature that in combination with the already selected feature maximizes the function f (with $m = 2$). The SFS adds 1 feature at a time until the best n features are obtained. In this selection, correlated features are omitted, ensuring a small intraclass variation and a large interclass variation in the space of the selected features. This approach works best with normalized features, that is, those that have been linearly trans-

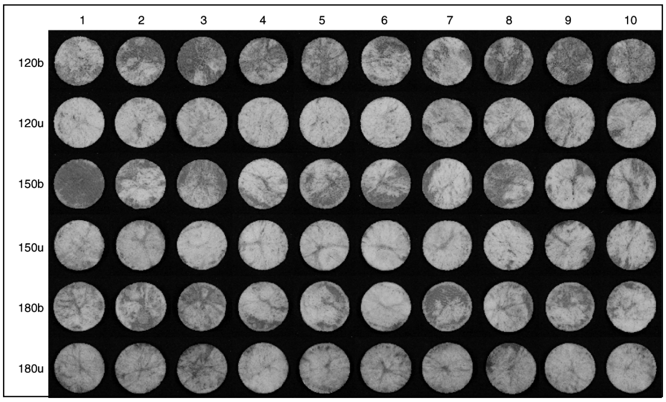

Figure 2—Grayscale images of potato chips processed under different conditions used for the classification process. Numbers placed horizontally indicates the sample number. Numbers and letter codes in the vertical axis indicate (1) frying temperature in °C (120, 150, and 180), (2) treatment of the slices before frying (u = unblanched; b = blanched).

Table 1—Extracted features from the images of potato chips. γ = geometric features; I = intensity features; R = red component features; G = green component features; B = blue component features, and L = *L*a*b features.**

Type	Feature	Description	Reference
γ	$(\bar{i}, \bar{j})$	Center of gravity	Castleman 1996
γ	h, w, A, L, R	Height, width, area, roundness, and perimeter	Castleman 1996
γ	$\phi_1 \ldots \phi_7$	Hu's moments	Sonka and others 1998
γ	$\lvert DF_0\rvert \ldots \lvert DF_7\rvert$	Fourier descriptors	Zahn and Roskies 1971
γ	$FM_1 \ldots FM_4$	Flusser and Suk invariant moments	Sonka and others 1998
γ	$FZ_1 \ldots FZ_3$	Gupta and Srinath invariant moments	Sonka and others 1998
γ	(a_e, b_e)	Major and minor axis of fitted ellipse	Fitzibbon and others 1999
γ	a_e/b_e	Ratio major to minor axis of fitted ellipse	Fitzibbon and others 1999
γ	α, (i_0, j_0)	Orientation and center of the fitted ellipse	Fitzibbon and others 1999
γ	G_d	Danielsson form factor	Danielsson 1978
I, R, G, B	G	Mean gray value	Castleman 1996
I, R, G, B	C	Mean gradient in the boundary	Mery and Filbert 2002
I, R, G, B	D	Mean s derivative	Mery and Filbert 2002
I, R, G, B	$K_1 \ldots K_3$	Radiographic contrasts	Kamm 1998
I, R, G, B	K_σ	Deviation contrast	Mery and Filbert 2002
I, R, G, B	K	Contrast based on CLP[a] at 0 ° and 90 °	Mery and Filbert 2002
I, R, G, B	Δ_Q	Difference between maximum and minimum of BCLP[a]	Mery 2003
I, R, G, B	Δ'_Q	$\ln(\Delta'_Q)$	Mery 2003
I, R, G, B	σ'_Q	standard deviation of BCLP[a]	Mery 2003
I, R, G, B	Δ''_Q	Δ'_Q normalized with average of the extreme of BCLP[a]	Mery 2003
I, R, G, B	$\bar{Q}$	Mean of BCLP[a]	Mery 2003
I, R, G, B	$F_1 \ldots F_{15}$	1st components of DFT of BCLP[a]	Mery 2003
I, R, G, B	$\phi'_1 \ldots \phi'_7$	Hu moments with gray value information	Sonka and others 1998
I, R, G, B	σ^2_g	Local variance	Mery and Filbert 2002
I, R, G, B	Tx_d	Mean (M) and range (Δ) of 14 IT features[b] with d = 1,2,3,4,5.	Haralick and others 1973
I, R, G, B	KL, DFT, DCT	64 first components of the KL, DFT, and DCT transform[c]	Castleman 1996
L	$L^*a^*b^*$	Color components of the region	Hunt 1991; Papadakis and others 2000

[a]CLP= crossing line profile, gray function value along a line that crosses the region at its center of gravity. The term BCLP refers to the best CLP, in other words, the CLP that represents the best homogeneity at its extremes (Mery, 2003).
[b]The following features are extracted based on a co-occurrence matrix of the whole image of the potato chips: 2nd angular moment, contrast, correlation, sum of squares, inverse difference moment, mean sum, variance of the sum, entropy of the sum, variance of the difference, entropy of the difference, 2 measures of correlation information, and maximum correlation coefficient, for a distance of d pixels.
[c]The transformation takes a resized window of 32 × 32 pixels, which includes the middle of the potato chips.

formed in such a way as to obtain a mean value equal to zero, and a variance equal to 1. In this way, the classifier only works with non-correlated features that provide information about the class of the object under test.

5. Classification. Six classes were established for the samples, namely 120b, 120u, 150b, 150u, 180b, and 180u, where the number represents the frying temperature in °C and b or u means blanched or unblanched, respectively. The corresponding 60 digital images are shown in Figure 2.

In statistical pattern recognition, classification is performed using the concept of similarity, meaning that similar patterns are assigned to the same class (Jain and others 2000), that is, a sample is classified as class "i" if its features are located within the decision boundaries of i. To perform the classification, a decision tree classifier was implemented (Safavian and Landgrebe 1991). In this classifier, a search is performed to select which feature can best separate one class from the rest. The feature is selected by maximizing the linear Fisher discriminant in this new 2-class problem. The separation is performed with a threshold, that is, if the feature is greater than the threshold, then the sample is classified as class x, otherwise the sample is classified as a super-class y, where y contains the rest of classes (except class x). The threshold is chosen by maximizing the classification performance defined as the ratio of the number of samples that were correctly classified to the total number of samples. The procedure is repeated for the super-class y, that is, a search of which feature can best separate one class of y from the rest of remaining classes of y, and so forth, until all original classes are classified. For a situation with n classes, n-1 thresholds are required.

Seven classification problems were studied: (1) classification of the 6 classes; (2) distinction between 120b and 120u, that is, to distinguish blanched from unblanched potato chips fried at 120 °C; (3) distinction between 150b and 150u; (4) distinction between 180b and 180u; (5) distinction between blanched and unblanched without considering the temperature; (6) classification of the 3 temperatures having only unblanched chips; and (7) classification of the 3 temperatures having only blanched chips.

Results and Discussion

In industry, the most common frying temperature for potato products is 180 °C. Recent findings show that acrylamide (a possible carcinogen in humans) formation in potato chips could be reduced significantly by decreasing the frying temperature (Haase and others 2003). Thus, we selected in this study, a medium (150 °C) and a low (120 °C) frying temperature. On the other hand, 2 pretreatments were also used: blanching and control (without blanching). In potato chip production, blanching is performed when the reducing sugar level of the raw potatoes is high and could lead to undesirable dark color after frying. Besides, it has been recently reported that decreasing the reducing sugar content by blanching could not only improve the color but also considerably diminish acrylamide formation in potato chips (Haase and others 2003).

The 10 gray scale images of potato chips acquired for each of the 6 conditions under study are shown in Figure 2. Roughness and color heterogeneity of the surfaces induced by the frying processes could be noted by the naked eye. The surface texture and the color of potato chips depended not only on the frying temperature but also on the pretreatment received by the slices before frying

Table 2—*L*a*b, area, and roundness features for the 6 classes of potato chips studied[a]**

Feature	120b	120u	150b	150u	180b	180u
$\{L^*\}_L$	62.94 ± 4.41	74.08 ± 2.99	65.02 ± 8.71	73.29 ± 2.90	67.28 ± 3.65	64.31 ± 3.72
$\{a^*\}_L$	–8.55 ± 0.49	-7.96 ± 0.53	–7.61 ± 0.55	–5.12 ± 1.52	–3.73 ± 1.55	6.05 ± 2.14
$\{b^*\}_L$	29.43 ± 1.42	29.95 ± 1.24	29.66 ± 1.83	30.62 ± 1.94	35.01 ± 1.79	43.15 ± 0.74
$\{A\}_I$	10.88 ± 0.52	11.84 ± 0.21	11.74 ± 0.17	11.62 ± 0.11	11.57 ± 0.21	11.86 ± 0.12
$\{R\}_I$	0.86 ± 0.006	0.87 ± 0.005	0.87 ± 0.005	0.87 ± 0.005	0.87 ± 0.007	0.84 ± 0.058

[a](1) 120, 150, and 180 represent the frying temperatures in °C; (2) u and b represent the treatment of potato slices before frying (u = unblanched; b = blanched).

Table 3—Classification performance of 6 classes the potato chips studied in 7 different cases[a]

Case	Classes	Nr of classes	Nr of samples	Feature 1 (best)	Feature 2	Feature 3	Feature 4	Performance
1	[120b], [120u], [150b], [150u], [180b], [180u]	6	60	$\{b^*\}_L$	$\{T_{x4}(\Delta_{11})\}_G$	$\{T_{x3}(\Delta_{14})\}_G$	$\{D\}_I$	90%
2	[120b], [120u]	2	20	$\{T_{x5}(\Delta_{11})\}_G$	—	—	—	100%
3	[150b], [150u]	2	20	$\{D\}_R$	$\{DCT_{71}\}_G$	—	—	100%
4	[180b], [180u]	2	20	$\{b^*\}_L$	—	—	—	100%
5	[120b,150b,180b], [120u,150u,180u]	2	60	$\{\sigma_g^2\}_R$	$\{DFT_{43}\}_I$	—	—	93%
6	[120b], [150b], [180b]	3	30	$\{a^*\}_L$	$\{T_{x1}(M_{12})\}_I$	—	—	100%
7	[120u], [150u], [180u]	3	30	$\{b^*\}_L$	$\{D\}_R$	—	—	97%

[a](1) 120, 150, and 180 represent the frying temperatures in °C; (2) u and b represent the treatment of potato slices before frying (u = unblanched; b = blanched).

(blanched or unblanched) as shown in Table 2. Statistical analysis shows that L^* depends on the pretreatment received but was independent of the frying temperature. For unblanched samples, L^* tends to decrease slightly as the frying temperature increases. On the other hand, L^* tends to remain almost constant with frying temperature for blanched samples (average L^* values were not significantly different at $P < 0.05$ for the 3 tested temperatures). a^* was affected not only by the oil temperature but also by the pretreatment received by potato slices. a^* values increased with frying temperature for both unblanched and blanched samples (from –7.96 to 6.05 and from –8.55 to –3.73, respectively). Finally, b^* was also affected by both frying temperature and the slice pretreatment, showing an increase with oil temperature either for unblanched or blanched potato chips (from 29.92 to 43.15 and 29.43 from to 35.01, respectively). L^* did not change significantly during frying, however a^* and b^* values increased considerably with the temperature of frying as a result of the Maillard reaction.

Major changes in area and roundness of the potato chips were not detected by visual inspection in spite of the large temperature range (60 °C) used for frying and the pretreatments studied (Figure 1). Results showed in Table 2 indicate that the values of area and roundness varied from 10.88 cm^2 to 11.86 cm^2 and from 0.84 cm^2 to 0.87 cm^2, respectively.

Results obtained for the 7 classification cases are summarized in Table 3. Although several features achieved good performance, only those with the highest performance value for each case, according to the Fisher discriminant function (Fukunaga 1990), are presented. Interestingly, the 7 classifications can be achieved at performances ≥ 90% using only 11 (of the 1511) features. In 6 cases, only 1 or 2 features suffice for the separation into classes. Many of the IT features were obtained from the co-occurrence matrix proposed by Haralick and others (1973), which exploits the intensity spatial dependence of the IT. The obtained Haralick features are range of the maximal correlation coefficient in the green image using 3 pixels of distance ($\{T_{x3}(\Delta_{14})\}_G$), mean of the 1st information measure of correlation grayscale image using 1 pixel of distance ($\{T_{x1}(M_{12})\}_I$), range of the difference entropy in the green image using 4 and 5 pixels of distance ($\{T_{x4}(\Delta_{11})\}_G$ and $\{T_{x5}(\Delta_{11})\}_G$). In addition, the coefficients of the discrete Fourier and Cosinus transformation of the grayscale and green images ($\{DFT_{43}\}_I$ and $\{DCT_{71}\}_G$), the mean 2nd derivative of the red and grayscale images ($\{D\}_I$ and $\{D\}_R$), and the local variance of the red image ($\{\sigma_g^2\}_R$) achieved a good separation performance in many of the studied cases. Finally, the $\{a^*\}_L$ and $\{b^*\}_L$ components are present in 4 of the 7 classification cases.

The classification process of the 6-class problem (case 1) is shown in Figure 3. The classification algorithm is as follows: (1) if $\{b^*\}_L > 40$, then the sample belongs to class 180u, else (2) if $\{T_{x4}(\Delta_{11})\}_G > 0.75$, then the sample belongs to class 120b, else (3) if $\{b^*\}_L > 32.5$, then the sample belongs to class 180b, else (4) if $\{T_{x3}(\Delta_{14})\}_G < 0.51$, then the sample belongs to class 120u, else (5) if $\{D\}_I > -0.022$, then the sample belongs to class 150b, else (6) the sample belongs to class 150u. In this case, only 6 of the 60 samples were misclassified.

To evaluate the performance of each classification, we use the ratio of the number of samples that were correctly classified to the total number of samples. We observe that in 5 of the 7 classification problems, the performance was between 97% and 100%, whereas in the other 2 cases, the performance was between 90% and 93%. Although the samples were highly heterogeneous, the correctly classification of the potatoes chips using a simple classifier and a few number of features was possible. Diaz and others (2003) have applied 3 different algorithms to classify olives in 4 quality categories. Their results showed that a neural network with a hidden layer was able to classify the olives with an accuracy of over 90%, whereas the partial least squares discriminant and Mahalanobis distance classifiers only performed at 70% accuracy. More sophisticated classification techniques can always be used; however, in this article we show that a simple classification technique is good enough to distinguish between the classes.

An analysis was carried out to determine the confidence interval for the performance obtained in the 1st classification problem where 6 classes need to be separated. The well-known cross-validation technique, widely used in machine learning problems, was used (Mitchell 1997). In cross-validation, some of the collected samples are removed and become the training set. Then, when training

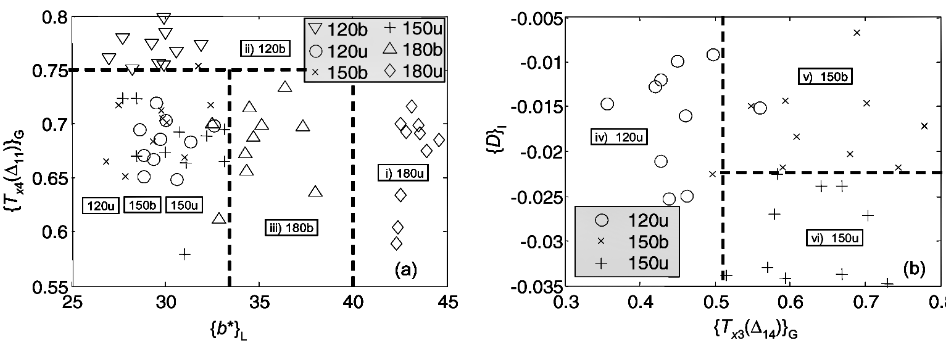

Figure 3—Threshold classification in 2 stages (a and b) of the 6 classes of potato chips studied according to the best performance features extracted. 120, 150, and 180 represent the frying temperatures in °C; u and b after the temperature values represent the treatment of potato slices before frying (u = unblanched and b = blanched). Roman numbers indicate the classes and the sequential steps that the classification followed.

is performed, the samples that were initially removed can be used to test the performance of the classifier on these test data. Thus, one can evaluate how well the method will classify potato chips that have not already examined. Confidence intervals, where the true value of performance is expected to fall, were obtained from the test sets (determined by the cross-validation technique) according to a *t* student test. In this problem, we have 6 classes and 10 samples per class. We removed the sample *k* in each class and we trained the classifier using the remaining 9 samples. The removed samples were used to test the classifier. The test classification performance was calculated. This experiment was performed 10 times by removing the *k*th sample in each class for $k = 1,\ldots,10$. The mean and the standard deviation of the 10 performances were computed yielding a mean performance of 83.3% with a standard deviation of 2.5%. According to the *t* student test with 9 degrees of freedom and 95% of confidence, we obtained that the performance of our classifier is 83.3% ± 5.6%, that is, the confidence interval is between 77.7% and 88.9% with 95% of probability. This result demonstrates the repeatability of the classification.

The methodology presented in this article is general and has the potential to be applied in the food industry if we are able to obtain from fried potatoes relevant human jury parameters of which color is one of the most important and correlated them with some of the features extracted as shown in Marique and others (2003)[1]. In this way, we will able to replace human operator classification by an automatic classification.

Some features extracted from 2D images could represent an economical alternative to topographical features for surface texture characterization. Among potential applications of this research are automatic quality control of potato chips based on computer vision and determination of surface roughness of potato chips from IT information in 2D images.

The methodology for automatic classification has a wide range of potential uses. Applied to potato chips, it could be used to assess the effect of potato cultivars, slicing methods, and frying conditions, among others. It can also be extended to study of the effect of raw materials and other unit operations used in the food industry when products exhibit heterogeneous external features (for example, color, roughness, shape).

Conclusions

Grayscale and color images of potato chips were useful to extract high-performance features for an appropriate classification. Eleven features were selected according to their classification performance. The selected features were either IT features or $L^*a^*b^*$ color features. No geometric feature was adequate for classification of potato chips because their values did not change significantly for the 6 different processing conditions used.

When 7 different classification cases were analyzed using the 11 selected features, potato chips were properly classified despite their high heterogeneity. According to the *t* student test with a cross-validation technique, the performance in the classification obtained for the 6 classes was in the confidence interval between 78% and 89% with a 95% probability.

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[1]Because our data and classes are different from those outlined in Marique and others (2003), it is not possible to establish an objective comparison of the performance between both approaches. However, there are 3 significant differences: (1) Marique and others (2003) use only gray level features based on mean values; a better performance could be obtained by measuring color features; (2) Marique and others (2003) extract features based on mean values only; it could be interesting to investigate other features like texture, for example; (3) Marique and others (2003) carry out the classification using an artificial neuronal network and a multiple linear regression yielding very similar performances in the validation data (89.9% and 87.8%, respectively); probably a small improvement in the performance could be achieved in our problem by using an artificial neuronal network.

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