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COMMUNICATION

Prediction of Mechanical Properties of Corn and Tortilla Chips by Using Computer Vision

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Abstract Deep-fat frying is a unit operation which develops unique sensorial attributes in foods. For instance, texture is the principal quality parameter of tortilla and corn chips. On the other hand, computer vision is a useful tool for quality evaluation and prediction of some physical properties in different either raw or processed foods. The objective of this research was to characterize corn and tortilla chips by using computer vision, and to build proper mathematical models which permit to predict mechanical properties of these chips (maximum force, such as hardness, and distance to maximum force, such as toughness) by using chromatic features extracted from their corresponding digital images. Corn and tortilla chips (thickness of 2 mm; diameter of 37 mm) were made from *masa* of maize and fried at constant oil temperatures of 160, 175, and 190 °C. A high linear correlation (R^2>0.9400) was obtained between mechanical properties and some image features (Hu, Fourier, and Haralick moments). Cross-validation technique demonstrated the repeatability and good performance (>90%) of the models tested, indicating that can be used to predict the textural properties of the tortilla and corn chips by using selected features extracted from their digital images, without the necessity of measuring them in a texture analyzer.

Keywords Mechanical properties · Tortilla chips · Computer vision · Image features · Frying · Texture of an image · Texture of foods

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Introduction

A nixtamalized soft moist dough called "*masa*" is the raw material used to make the most popular *masa*-based-snack products which are very known in the market such as corn and tortilla chips. Corn chips are fried directly from *masa* and contain 20% more oil than tortilla chips (Moreira et al. 1997). On the other hand, tortilla chips are first baked and then fried, a procedure which makes them to absorb less oil during frying and cooling, to develop crispier textures, and to acquire a stronger alkaline flavor than corn chips (Kawas and Moreira 2001). Mechanical properties such as crispness, hardness, etc. are some of the most significant quality characteristics of the texture of corn and tortilla chips since they mainly contribute to the overall quality and acceptability by consumers (Moreira et al. 1997). The texture of corn and tortilla chips depends on several factors such as: raw material, maize variety, endosperm texture and type, pre-treatments and frying conditions, packaging conditions, storage, and time conditions, among others (Bedolla and Rooney 1982).

Computer vision (CV) is a non-destructive and objective tool which is used to: (1) measure quality attributes such as color in bakery products, potato, and tortilla chips (Gunasekaram and Ding 1994; Brosnan and Sun 2003; Pedreschi et al. 2004 and 2006; Mery and Pedreschi 2005; Mery and Soto 2008; Mery et al. 2010), (2) inspect automatically the quality of raw vegetables, fish, and meat (Cubero et al. 2011; Zheng et al. 2006; Quevedo and Aguilera 2010; Arzate-Vázquez et al. 2011). Several digital features can be extracted from digital images such as chromatic features (Pedreschi et al. 2004; Mery and Pedreschi 2005; Mery and Soto 2008), geometrical and textural features (Mery and Soto 2008). The texture of an image (which is different to the texture of foods which describes specifically the mechanical properties of the foodstuffs) is a term used in CV to characterize the spatial distribution of gray levels in a neighborhood in a digital image. Besides, the texture of an image is defined as repeating patterns of local variations in image intensity which are too fine to be distinguished as separate objects at the resolution of the observation scale; this is the local variation of brightness form 1 pixel to the next or within a smaller region (Zheng et al. 2006: Mery and Soto 2008).

The objective of this research was to characterize the mechanical behavior (measured by maximum force, MF, and distance of penetration, MFD) of corn and tortilla chips during frying at different temperatures, and to obtain good correlations between their mechanical properties and their corresponding digital features extracted from their digital images, in order to build trustable models which allow predicting mechanical properties of tortilla and corn chips by using the image features extracted from their digital images (without the necessity of measuring them in a texture analyzer).

Materials and Methods

Sample Preparation

Corn and tortilla chips were made from "*masa*" of maize (F. H.M. Alimentos Ltd., Santiago de Chile, Chile). The thickness of chips was fitted to 2.0±0.2 mm by using a tortilla machine (González, S.A., Guadalupe, México). A circular cutting mold was used to provide chips with a diameter of 37±2 mm. Tortilla chips were first baked on an electric iron skillet (Black and Decker) by heating them at 215 °C for 30 s, and then, flipped, cooked for 30 s, flipped again, and cooked for 30 s in order to be finally fried.

Ten chips (corn or tortillas) per sampling time were deep fried in 4 l of hot fresh sunflower oil (Chef®, Coprona, Chile) contained in an electrical fryer (Beckers, Model F1-C, Italy). Chips were fried at different time intervals according to the frying temperature: 160 °C (0, 36, 72, 108, 144, 180, and 220 s), 175 °C (0, 10, 20, 50, 80, 110, and 140 s), and 190 °C (0, 5, 15, 30, 45, 60, and 80 s). The temperature of frying was kept constant (±1 °C) at the set frying temperature and it was measured inside the oil bath by using a thermocouple (mod. GG-30-KK, Tersid, Milano, Italy) connected to a digital data logger (Model 2700, Keithley, Cleveland, USA). The oil was preheated for 1 h prior to frying, and discarded after 6 h of use (Blumenthal 1991). Then, the fried chips were cooled down to room temperature in desiccators during 10 min before being analyzed. Experiments were run in triplicate (total n=30; 10 chips per run at each sampling time). Water content of the chips was determined gravimetrically by drying samples of 5 g at 160 °C until constant weight in a convective oven (MS-70, A&D Company Ltd., USA). Resulting values of moisture content were expressed in percentage of dry basis.

Computer Vision Analysis

The computer vision system used in this research was set up according to Pedreschi et al. (2006). The white balance of the camera was set using a standardized gray color chart from Kodak (Boston, MA). In order to calibrate the digital color system, the color values (L*a*b* scale) of 35 color charts were measured simultaneously by using a colorimeter and by computer vision using Balu Toolbox, which was calibrated in order to calculate the same L*a*b* color values previously measured by the colorimeter (León et al. 2006; Mery et al. 2010). Color charts were photographed and analyzed periodically in order to ensure that the lighting system and the color digital camera were working properly.

Each sample removed from the fryer at each frying time and cooled, was placed in front of the camera in the same position, and two images (front and back) from each sample were obtained (n=60). All images were acquired at the maximum camera resolution (2272×1704pixels) and the same conditions by using the computer program Zoom-Browser v6.0 (Canon, Intel, Santa Clara, CA, USA). The acquired images were saved as TIFF-24bit files and retrieved later for subsequent digital image analysis.

Feature Extraction

For digital image analysis and feature extraction operations, we used the Balu Toolbox[1] (Mery and Soto 2008) which is a program built with Matlab software (Mathworks 2003).

[1] Balu Toolbox can be downloaded from http://dmery.ing.puc.cl.

Balu Toolbox allowed performing digital image analysis and pattern recognition operations by extracting 672 chromatic and geometric features from digital images previously segmented to separate the sample (zone of interest) from the background. This toolbox also allowed correlating the best extracted features of the total features analyzed versus the mechanical experimental parameters (MF and MFD). 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 was 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 corresponded to the area where the tortilla chip was located. Subsequently, feature extraction is concentrated principally around the measurement of chromatic properties extracted from the intensity image and the color features from the RGB images. Table 1 shows the principal intensity features that provide information about the color intensity of a tortilla or corn chip region extracted for each color channel, following by four groups of features (totally, 618 intensity features).

Mechanical Property Analysis

Chips were analyzed at 20 °C by a puncture test performed in a Texture Analyzer™ (TA.XT2, Texture Technology Corp., NY, USA) using a 1/4-in. diameter ball probe at 1 mm/s until it cracked the sample. The chips were supported along the periphery during measurements of texture. Force against distance curves were determined for each sample using Texture Expert software (v 6.06), and the resulting averaged curves were used to define the value of each of the mechanical parameters analyzed: (1) The MF required to break the sample (principal peak), which is related to hardness (Bourne 2002); (2) The distance value (MFD) until the maximum force was obtained which is related to toughness (Vincent 1998). Mechanical measurements of each chip were made in batches of ten chips at each experimental condition and run in triplicate (n=30 per sampling point).

Statistical Analysis

Differences between means of data for each treatment were compared by Student’s t test using GraphPad Prism v.4.0 program (GradPad Systems Inc.). Statistical significance was expressed at the $p<0.05$ level. A statistical analysis was carried out to determine the confidence interval for the performance obtained. Besides, the well-known cross-validation technique which is useful in classification of potatoes chips using pattern recognition techniques (Pedreschi et al. 2004, 2006; Mery and Pedreschi 2005) and quality classification of corn tortillas (Mery et al. 2010), was used. This validation technique of k–partition=N/F permits the evaluation of prediction model in order to obtain a robust model and accurate error. In cross-validation, some of the collected samples are removed and become the training set. The data is divided into F folds randomly. Each group contains N/k samples, where N is the total number of samples of the data. Then, F-1 folds are used as training data and the remaining fold is used as testing data to evaluate the performance of the estimation. When training is performed, the samples that were initially removed can be used to test the performance of the mathematical model on these testing data. Thus, one can evaluate how well the model works with samples that have not been already examined. This process is performed (F-1) more times, rotating training and test data during each cycle. The F individual performances from the folds are averaged to estimate the final performance. In our case, the data consists of 3 temperatures and 30 samples (N) per temperature for each mechanical properties studied

Table 1 Extracted features by Balu Toolbox from Matlab software (Adapted by Mery et al. 2010)

Family	Group	Name of features
Color (gray, red, green, blue, hue, saturation, value, L*, a*, b*)	Standard	Mean intensity, standard deviation intensity, standard deviation intensity with neighbor, mean Laplacian and mean gradient
	Statistical textures	Tx (k,p) (mean/range) for k=(1) angular second moment; (2) contrast; (3) correlation; (4) sum of squares; (5) inverse difference moment; (6) sum average; (7) sum variance, entropy; (8) sum variance; (9) entropy; (10) difference variance; (11) difference entropy; (12, 13) information measures of correlation; and (14) maximal correlation coefficient; and p=1,…, 5 pixels.
	Filter banks	Discrete fourier transform, DFT (1, 2; 1, 2) and discrete cosine transform, DCT (1, 2; 1, 2) coefficients
	Invariant moments	Int-Hu (1,…, 7) Hu moments with intensity information

Coefficients without units

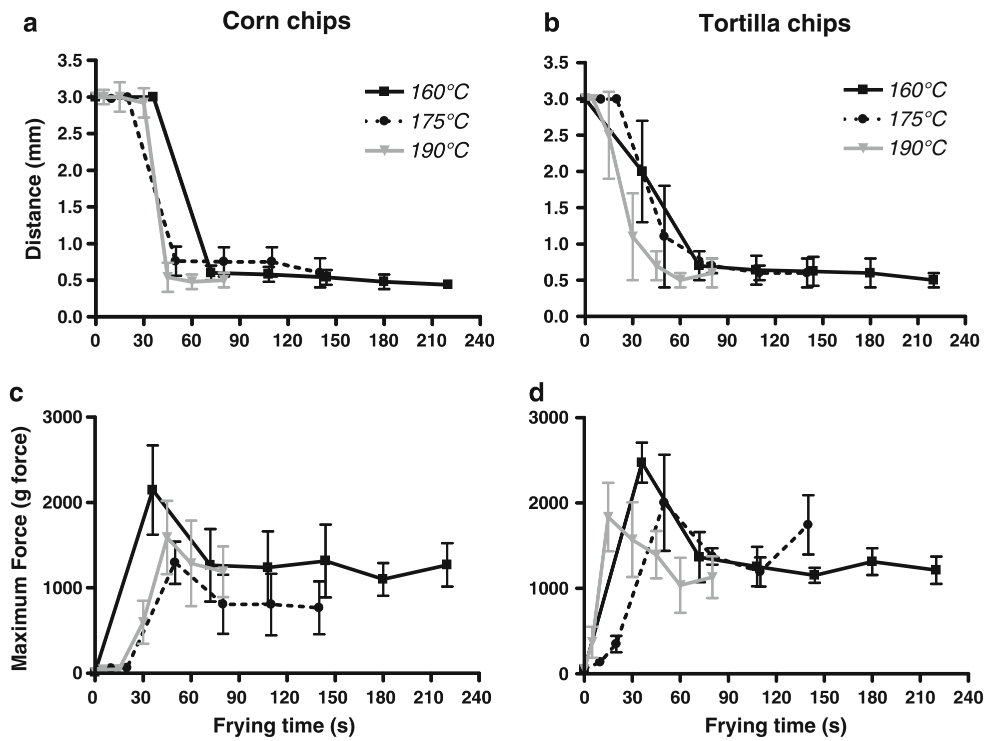

Fig. 1 Mechanical parameters (distance—MFD, and maximum force—MF) obtained using the texture analyzer corn and tortilla chips (**a**,**c** and **b**,**d**, respectively). *Error bars* indicate standard deviation of three replicates. Each *point* for each replicate corresponds to ten samples

during frying time and 60 digital images. For these experiments, we choose $F=10$ folds and we removed the sample k ($n=6$) and we trained the model using the remaining 54 (N-k) samples. In each test, the testing data corresponds to a different group, and the error obtained in each experiment is called e_k, for $k=1, \ldots, 10$. The F individual performances from the folds were used to estimate the final performance of the model. The percent of success of the mathematical model obtained of each sample condition was determined comparing statistically instrumental and mathematical data obtained for test data, and not significant differences ($p>0.05$) was obtained between data using Dunnett's test and t test with 10 degrees of freedom and 95% of confidence.

Results and Discussion

Two different pattern behaviors of mechanical parameters for crispy or dough structure were obtained. The distance of penetration (MFD) was maximum (3 mm) at high water content and low frying time (first time of frying evaluated in all temperatures) producing a deformed chip whose structure could not be broken by the ball probe due to their dough structure and ductile solid behavior, not only in corn but also in tortilla chips (Fig. 1a, b). However, the MFD diminished with frying time, in brittle and crispy chips (Fig. 1a, b) due to the fact that the probe breaks the chips, obtaining higher MF and lower MFD than those corresponding to dough structures, according to results obtained by Moreira et al. (1995) in tortilla chips fried at 190 °C. These results could be explained by the lower water content in tortilla chips (53±2%dry basis (db)) than in corn chips (83±2%db).

The variation in mechanical property data was high, as showed by considerable standard deviations and scattering of the data (10–20%). These results are in agreement to those previously obtained by Kayacier and Singh (2003) and Moreira et al. (1997) in nixtamalized-based chips by using compression test, where irregular surfaces of samples

Table 2 Best correlation between mechanical (maximum force, x) and digital features (y) obtained by image analysis using computer vision for corn and tortilla chips

Chips	Frying temperature	Digital features (y)	R^2	Cross-validation (%)
Corn	160 °C	Tx8, $d1$ (mean)—a*	0.9703	100
	175 °C	Mean intensity—value	0.9395	90
	190 °C	Standard intensity-N—red	0.9795	100
Tortilla	160 °C	Invariant Hu moment 7—Value	0.9796	100
	175 °C	Fourier 1—Value	0.9801	100
	190 °C	Tx1, d3 (range)—Gray	0.9662	90

R^2 is calculated correlation coefficient by linear regression; *cross-validation* is percent of success from ten performances

Table 3 Best correlation between mechanical parameter (distance MFD, x) and digital features (y) obtained by image analysis using computer vision for corn and tortilla chips

Chips	Frying temperature	Digital parameter (y)	R^2	Cross-validation (%)
Corn	160 °C	Tx11, d5 (range)—a*	0.9939	90
	175 °C	Tx3, d5 (mean)—blue	0.9300	100
	190 °C	Tx5, d1 (range)—a*	0.9877	100
Tortilla	160 °C	Invariant Hu moment 7—gray	0.9829	100
	175 °C	Tx12, d4 (mean)—blue	0.9775	90
	190 °C	Tx13, d2 (range)—b*	0.9509	100

R^2 is calculated correlation coefficient by linear regression; *cross-validation* is percent of success from ten performances

made mechanical measurements more difficult to perform than in homogeneous foods with regular surfaces. The obtained coefficient of variation (defined as 100×standard deviation/mean value) changed for each frying time, oil temperature, and tortilla type. The variation coefficient was in the range of 5% to 10% for MFD and 10% to 20% for MF, observing the lowest variation coefficient for tortilla chips. The reasons for this high variation in the food texture data could be attributed: (1) the shape of the samples was not uniform and the edges of some of them were little bent; (2) some samples puffed more than others; this fact was observed even though all replications were fried for the same time at one constant temperature. Pre-baked samples (tortillas) are less puffed than corn chips (data not shown) and showed lower variation coefficients; (3) heterogeneous structure of the obtained *masa* due to the nixtamalization process between replicates.

The mean of each digital feature (n=60) obtained from digital image analysis for chips fried at the same time each oil temperature was correlated with the data mean (n=30) of each mechanical parameter obtained by using the texture analyzer. Thus, the software searched the best digital feature that lineally correlated (R^2>0.9500) with the mechanical parameter at each temperature, as observed in Tables 2 and 3 for MF and MFD, respectively. These selected digital features for each mechanical parameter tested, were different not only with oil temperature but also with tortilla type, principally due to the lower water content in ~40% of tortilla chips. By using the linear equations obtained from the best digital correlation in each case, the mathematical model, which could permit the prediction of mechanical parameters (MF and MFD), was calculated for each replicate. Figure 2 shows an example of the maximum force of tortilla chips fried at 190 °C, where a high correlation (R^2≥0.9600) was obtained between the MF instrumentally measured and predicted by using the mathematical linear model obtained from the extracted feature (theoretical parameter). This high linear correlation (R^2≥0.9400) was obtained for both corn and tortilla chips in each of the tested conditions.

Therefore, a cross-validation technique was used in order to validate each mathematical model obtained for predict each mechanical parameter at each frying condition. The percent of success of each linear model to predict each mechanical property using the corresponding digital feature was higher than 90% (Tables 2 and 3), being mostly 100%. Besides, Bartlett's test for equal variances showed not significant differences (p>0.05) between variances of the prediction model and the experimental data and between the test classification performance. The results of Student's t test showed that the performance of the prediction models was 96.6±4.5%. The variation coefficient of data obtained by models comparing to experimental data was lower than 5% in all studied cases. This result suggests the repeatability and effectiveness of the linear model to predict the mechanical properties using digital features and the good fitting of its prediction.

Conclusions

The principal differences on the mechanical behavior between corn and tortilla chips can be attributed to the minor initial water content in tortilla chips (53%db) than in corn chips (89%db) and to the oil temperature used in frying. A high linear correlation (R^2>0.9400) between mechanical parameters and digital features extracted from

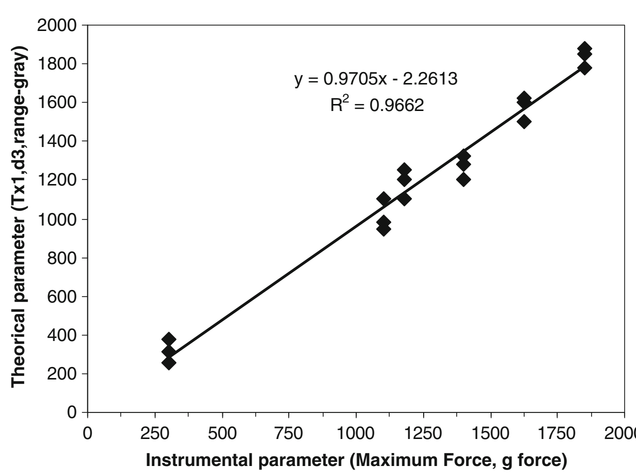

Fig. 2 Correlation between theoretical parameter of maximum force of tortilla chips fried at 190 °C obtained from the selected digital features and the corresponding instrumental parameter measured using the texture analyzer

the corresponding samples was obtained. According to the cross-validation technique, the performance in the prediction obtained was ~96% and the coefficient variation lower than 5% demonstrating the repeatability and effectiveness of linear model to predict mechanical properties using digital features and good fitting of the prediction. This tested procedure could be implemented to improve and control the frying process of tortilla chips.

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