Chapter XXII

Quality evaluation and control of potato chips

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Chapter XXVI

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1 INTRODUCTION

Global consumption of potato as food is shifting from fresh potatoes to added-value, processed food products. In this sense, potatoes are grown in over 110 countries throughout the world representing one of the most important staples of the human diet (Bradshaw & Ramsay, 2005). Potatoes are processed into a great variety of products, including: cooked potatoes, par fried potato strips, French fries, potato chips, potato starch, potato granules, potato flakes, dehydrated diced potatoes, among others (Pedreschi, 2012). Potatoes with high solids content (20–22%) are preferred for frying because they result in better texture, higher yields, and lower oil absorption in the finished product. In addition, a low reducing sugar content is required (<2.5–3 mg of reducing sugar per gram of potato) to minimize color development during frying of potato chips, which is generated by the non-enzymatic Maillard browning reaction (Lisinska & Leszczynski, 1989).

Potato chips are very thin pieces of sliced raw potatoes that are fried to a final oil and moisture content of ~35% and 1.8%, respectively (Moreira et al., 1999). Drying in hot oil at temperatures between 160 C°C and 180 °C is characterized by drying rates that are too high (Baumann & Escher, 1995). This fast drying is critical to improve the mechanical and structural properties of the final product. On the other hand, par fried potatoes and French fries are traditionally produced by cutting potato strips from fresh potatoes (parallelepiped of 1x1 cm cross section by 4 to 7 cm in length), which are then deep-fat fried. Two major kinds of strips are produced at a commercial scale: 1) deep-frozen completely fried strips, which just require oven heating, 2) deep-frozen partially fried chips, which require additional frying before eating and (Bouchon, 2002; Lisinska & Leszczynski, 1989). French fry represent a composite structure formed by two regions: (1) an external dehydrated and crispy surface where oil is located and (2) a humid and cooked core free of oil (Pedreschi, 2012). The external crust is very similar to the structure of a fried potato slice or potato chip (Bouchon 2002; Pedreschi et al., 2001). The final oil and moisture content of French fries is approximately 15% and 38%, respectively (Aguilera & Gloria-Hernández, 2000).

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 at al., 2005). The color of potato chips is the first quality parameter evaluated by consumers and is critical in the acceptance of the product, even before it enters the mouth (Pedreschi et al., 2006). Color of potato chips changes during frying as the potato components are restructured during processing and color surface reflects not only the heterogeneous surface formed as a result of frying of potato slices but also the non-homogeneous oil distribution in potato chip surface.

On the other hand, acrylamide has been reported as a critical compound for human health (carcinogenic in rats) that is formed in potatoes during frying and that is highly related to the color of the potato chips (Rosen and Hellenäs, 2002; Mottram and Wedzicha, 2002; Stadler et al., 2002; Pedreschi et al., 2005). Potato chip color is mainly result of the Maillard reaction that 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). Generally, potato tubers which contain more than 2% of reducing sugars are discarded for frying since they can generate too dark colorations during the processing (Lisinska and Leszczynski, 1989). Researching has demonstrated that 2.5-3 mg of reducing sugar per gram of potato should be the maximum value accepted for potato chip preparation. Since Maillard Reaction in mainly not only the responsible of the desired flavor, taste and color of fried potatoes, but also of potato chip acrylamide content, an interesting challenge arises in how to mitigate acrylamide formation in potato chips without

affecting negatively their attractive sensory attributes and thus, their consumer acceptance (Pedreschi, 2012)

Traditionally the potato chip color has been measured instrumentally with special devices called colorimeters. Recently, potato chip color has begun to be measured with systems based on digital image processing (Segnini et al., 1999; Pedreschi et al., 2004). Quality of potatoes in chip industry is estimated from the intensity of darkening during frying which generally is measured by a human jury, subject to numerous factors of variation. Marique at al., (2003) measured gray level intensities of different parts of potato chips by using image analysis and then they tested an artificial neural network, to associate these data with color categories. In European factories, some computer vision systems have been tested the on-line evaluation of potato chips, allowing chips to be sorted according to defects like black spots or blisters. Some researchers have been also working on a promising device that should be able both to classify chips according to color and to predict acrylamide levels using neural networks. Researchers in this topic are also routinely providing classical visual evaluation against a standard chart, and they did a good amount of work to describe which criteria are really taken into account by the operator (overall appearance, heterogeneity, contrasted extremities, etc.) to evaluate the potato chip surface. In this chapter, the application of computer vision to study the quality attributes of potato chips in a simple way will be emphasized.

2 COMPUTER VISION

Computer vision (CV) is playing an increasingly important role in automated visual food inspection and it is a novel technology for acquiring and analyzing an image of a real scene by computers and other devices in order to obtain information or to control processes (Mery et al., 2013). In this sense, considerable research efforts in computer vision applied to food quality evaluation have been developed in the last years; however, they have been concentrated on using or developing tailored methods based on visual features that are able to solve a specific task (Mery et al., 2013).

In the last years, considerable research efforts in visual food quality evaluation have been concentrated on using or developing ad-hoc features and classifiers that are able to solve a specific task. The traditional strategy to solve this problem is to use a low number of features and a few number of classifiers, because the cost is considerably reduced for experimenting, training and testing. Using today's computer capabilities, however, it is now possible to extract a very large number of features and to test several state-of-art classifiers, in order to select which features are really relevant and at the same time which classifier achieves the highest performance for these selected features It is clear that the recent progress in computer technology allows the handling of various theoretical and experimental problems in science and technology, which were inaccessible before. Currently, the processing of many large images, the use of sophisticated filters in digital image processing, the extraction of a large set of features in different color spaces, and the test of many optimization algorithms—to cite a few—are possible (Mery et al., 2013).

Basically, a computer vision system (CVS) consists of a digital or video camera for image acquisition, standard settings illuminants, and computer software for image analysis (Papadakis et al., 2000; Brosnan and Sun, 2004). Figure 1 shows a schematic representation of a general CV pattern recognition process required for the automatic classification of potato chips which involves the five steps (Castleman, 1996; Mery et al., 2003): image acquisition, image pre-processing, image

segmentation, feature extraction and classification. The last four steps include several algorithms of image processing, pattern recognition and computer vision. They all are implemented in a Matlab Toolbox for research purposes (Mery, 2011) with promising results in numerous computer vision applications on quality evaluation of foods such as quality control of tortillas (Mery, 2010). Each step of the computer vision system is described in the following:

(i) Image acquisition: A digital image of the food under test is taken (sometimes resized) and stored in a computer (Mery et al., 2013). When acquiring images it is important to consider the effect of illumination intensity and the specimen's orientation relative to the illumination source since the gray level of the pixels is determined not only by the physical features of the surface but also by these two parameters (Peleg, 1993; Chantler, 1995). Typically, a color digital camera provides three digital images, namely, red [R], green [G] and blue [B] digital images. Figure 2 shows an image acquisition system implemented by Pedreschi et al., (2004) to measure the different quality attributes in potato chips. This system is composed of: (i) A color digital camera 4 of Mega pixels of resolution; (ii) Four Natural Day-light 18W fluorescent lights (60 cm in length), with a color temperature of 6500 K, and a color index (Ra) close to 95% for proper illumination; (iii) A wooden box where the illuminating tubes and the camera were placed; the interior box walls were painted black to minimize background light (León et al., 2006).

(ii) Image pre-processing: The digital image is improved in order to enhance the details before they are analyzed (Mery et al., 2013). 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].

(iii) Image segmentation: The food image is found and isolated from the background of the scene (Mery et al., 2013). The intensity image is used to divide the images into disjoint regions with the purpose of separating the part of interest from the background. This segmented image [S] is a binary image, where '0' (black) and '1' (white) means background and object respectively. In our case, such region of interest corresponds to the area where is located the potato chip under test. Mery & Pedreschi (2005) developed a robust algorithm to segmenting food image from a background in several color images.

(iv) Feature extraction: Significant features of the food image are quantified (Mery et al., 2013). 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, etc.), and on the intensity and color characteristics of regions (mean value, gradient, second derivative, texture features, etc.). The geometric features are computed from the segmented image [S], the intensity features are extracted from the grayscale 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 carried out. In order to reduce computational time required in the pattern recognition process it is necessary to select the features that were relevant for the classification. For this reason, a feature selection must be performed in a training phase.

(v) Classification: The extracted features are interpreted automatically using knowledge about the analyzed food in order to evaluate its quality (Mery et al., 2013). 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 can 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 employ neural networks or fuzzy logic (Castleman, 1996; Jain et al., 2000; Mery et al., 2003). In statistical pattern recognition for example, classification is performed using the concept of similarity: patterns that are similar are assigned to the same class (Jain et al., 2000), i.e., a sample is classified as class 'i' if its features are located within the decision boundaries 'i'. In order to perform the classification, a *Decision Tree Classifier* was implemented (Safavian and Landgebe, 1991). In this classifier, we search which feature can separate one class from the rest of classes at best.

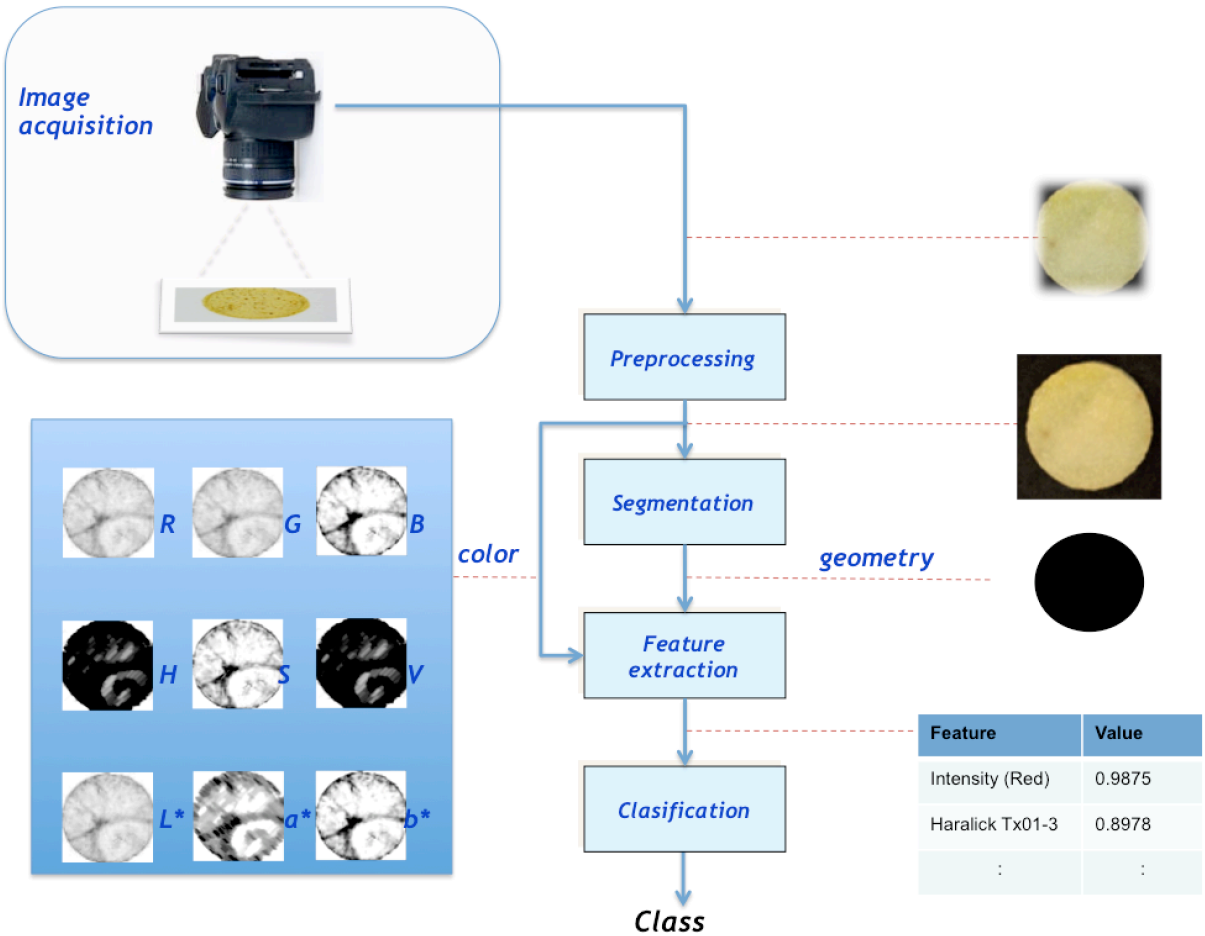


Figure 1. Schematic representation of the pattern recognition process required for the automatic classification of potato chips.

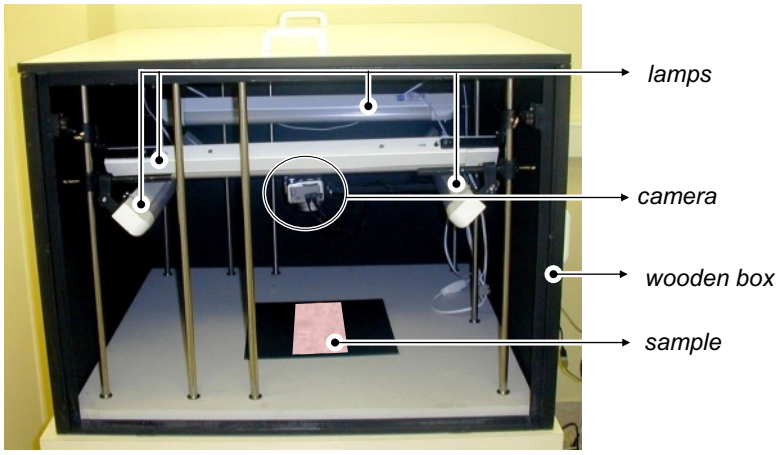


Figure 2. Image acquisition system implemented to evaluate potato chip quality. (Reprinted from *Food Research International*, available on line, Katherine León, Domingo Mery, Franco Pedreschi, Jorge León). Color measurement in *L*a*b** units from RGB digital images. Copyright 2006, by courtesy of Elsevier).

3 IMAGE FEATURES

Image feature extraction is one of the most active and research topics in computer vision. According to the diverse information stored in pixels, image features obtained can be categorized into four kinds: color, size, shape and texture (Du and Sun, 2004). Image features have been extensively applied in the potato industry for quality evaluation and inspection potato chips (Pedreschi et al., 2004). However, there is still a lack of a universal method that can be proposed to obtain the most proper features for complex foodstuffs such as potato chips. It is difficult to determine the optimal method for image feature extraction in potato chips.

In the last years, CV has been used to measure objectively the color of potato chips since they provide some obvious advantages over a conventional colorimeter, namely, the possibility analyzing simultaneously the whole surface and the details of the chip, and quantifying characteristics such as brown spots and other appearance defects in the surface (Figure 3). Color in CV is the intensity of pixels, while size reflects the number of pixels and shape describe the boundary of food products. Color features can generally be extracted from different color spaces such as RGB (red, green, blue) and HIS (hue, saturation, intensity) using statistical means. Color features are effective tools for indicating changes of components of potatoes during frying (Pedreschi et al., 2005).

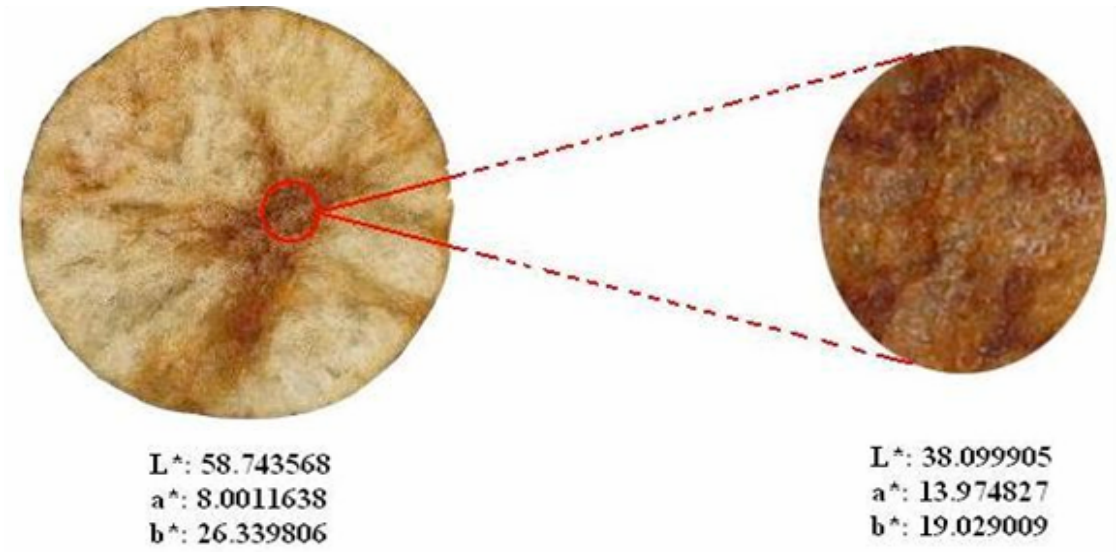


Figure 3. Color of a complete potato chip and of a small circular browned region of it in *L*a*b** units. (Reprinted from *Food Research International*, available on line, Franco Pedreschi, Jorge León, Domingo Mery, Pedro Moyano). Development of a computer vision to measure the color of potato chips. Copyright 2006, by courtesy of Elsevier).

In image analysis for food products, color is an influential attribute and powerful descriptor that often implies object extraction and identification and that can be used to quantify the color distribution of non-homogeneous samples (Brosnan and Sun, 2004). The use of CV for color quality assessment require an absolute color calibration technique based on a common interchange format for color data and a knowledge of which features from an image can be best correlated with product quality. Rapid advances in hardware and software for digital processing have motivated several studies on the development of CVS to evaluate the quality of diverse potato processed products such as potato chips. For instance, a pattern recognition approach was used for classification of potato chips processed under six different conditions obtained good classification performance (Pedreschi et al., 2004). On the other hand, Marique et al., (2003) modeled the color classification of potato chips by image analysis and artificial neural networks obtaining correlation coefficients of 0.972 for training data and of 0.899 for validation data.

Color of potato chips has been measured using computerized video image processing by mean of gray level values (Scanlon et al. 1994). A computer-based video system was developed to quantify the color of potato chips in the *L*a*b** color space (Segnini, Dejmek and Öste, 1999). León et al. (2006) developed a methodology for obtaining accurate device-independent *L*a*b** color units from device-dependent RGB color units captured by a digital color camera based on modeling the transformation of coordinates of the RGB color space into coordinates of the L*a*b* color space so that the values delivered by the model are as similar as possible to those delivered by a colorimeter over homogenous surfaces. Pedreschi et al., (2006) design and implement a computer vision system to measure representatively and precisely the color of potato chips in *L*a*b** units from RGB images.

Size features are usually obtained using measurements of area, perimeter, length and width, and are more preferable for evaluating the variation of the size of the potato slices during frying (Pedreschi et al., 2004). Shape features are generally proposed to inspect the acceptance of potato chip shape to customers and the variation of shape during frying. Shape is characterized in two ways, i.e., size dependent measurement such as compactness and elongation, and size independent measurement such as spatial and Fourier descriptors. Since digital images can are composed of pixels, two primary features, i.e., area and perimeter can be acquired by counting the number of pixels in images and by summing the distance between every two neighbouring pixels on the boundary, respectively. Length and width are another two measurements of size. Size features from images can effortlessly measure the size of the products almost instantly.

Shape is another important factor that affects the decision of customers on purchasing; therefore, shape features are important for computer vision to grade food products. Typically, shape features are obtained from images to characterize the shape of food products in order to study the changes of shape during processing, or to evaluate the acceptance of product shape for customers. Shape is generally referred to as the profile of physical structure of objects geometrically. Some of the popular shape measurements applied in the food industry are: (i) Compactness which is the ratio of area over the square perimeter. (ii) Elongation which is the ratio of major axis over the minor axis. (iii) Convexity which is the ratio of convex perimeter over the perimeter. (iv) Roughness which is the ratio of area over the square major axis.

Finally, texture could be a potential indicator of sensory, chemical and physical properties of potato chips and it has found that texture mostly contained more information about chemical and physical properties than color and size. Texture is normally the dependency between pixels and their neighboring pixels or the variation of intensity of pixels. Texture features of images describe the textural patterns of properties coarseness, fineness, granulation, randomness, lineation, and hummocky of the surface of the food products (Haralick et al., 1973). In the analysis of texture, four different methods, i.e., statistical texture, structural texture, transformed-based texture, and model-based texture, are available so far.

Textural properties, which explain details of how the surfaces are composed and structured by the dependency of pixels from each other or by the intensity variation across pixels. Texture features can be used for quality inspection of potato chips. Textures features can be acquired from images taken from the surface of a potato chip samples by using video cameras. Other identical set of samples of potato chips is used to obtain the quality attributes of the samples using sensory panelists or instruments. Afterwards, learning models, e.g., statistical learning, fuzzy logic, and neural networks, can be set up to correlate the texture features to the potato chip quality. Based on the information obtained from the learning models, different categories of potato chip quality can be finally predicted by using their texture features from the images (Pedreschi et al., 2004).

Computer analysis of surface textures of foods is of interest because many processes depend on their complexity. For instance, there is a known dependence between the oil uptake and the surface properties of fried potatoes (Pedreschi et al., 2000; Bouchon, 2002). Visual textures are generally formed by the interaction of light with a rough surface such as that of fried potatoes. Scale-sensitive fractal analysis has been applied directly over topographical data sets (heights as a function of position) to quantified important changes in parameters describing surface texture of potatoes during frying such as the area-scale fractal complexity (Asfc) and the smooth-rough crossover (SRC). Other way to perform fractal analysis or other kind of analysis to quantify textural properties of a surface is using the information contained in images (brightness as a function of position) with the disadvantage that in this case the

topography of the sample is not necessarily correlated with the texture of its surface image (Quevedo et al., 2002; Rubnov and Saguy, 1997).

Different features of color, size, shape, and texture are combined together for their applications in the food industry because in this way, they increase the performance of the methods proposed. For instance, coefficients for the principal component regression (PCR), partial least square regression (PLSR), and neural network increase if we add a texture feature. These features could be applied in various kinds of food such as fried potatoes for detection and segmentation of surface defects, prediction and characterization of chemical and physical properties, and evaluation and determination of sensorial characteristics (Pedreschi et al., 2004).

Features extracted from potato chip images by Pedreschi et al. (1994) are described in Table 1 and have been grouped into six 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). The details of how these features are calculated can be found in the references of Table 1 as well**.**

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. (Reprinted from *Journal of Foood Science*, Vol. 69, Franco Pedreschi, Domingo Mery, Fernando Mendoza, José Miguel Aguilera. Classification of potato chips using pattern recognition. Pages 264-270, Copyright 2004, by courtesy of Institute of Food Technologists).

Type	Feature[4]	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	$\phi_1 \cdots \phi_7$	Hu's moments	Sonka and others 1998
γ	$\lvert DF_0\rvert \cdots \lvert DF_7\rvert$	Fourier descriptors	Zahn and Roskies, 1971
γ	$FM_1 \cdots FM_4$	Flusser and Suk invariant moments	Sonka et al., 1998
γ	$FZ_1 \cdots FZ_3$	Gupta and Srinath invariant moments	Sonka et al., 1998
γ	(a_e, b_e)	major and minor axis of fitted ellipse	Fitzibbon et al., 1999
γ	a_e / b_e	ratio major to minor axis of fitted ellipse	Fitzibbon et al., 1999
γ	α , (i_0, j_0)	orientation and center of the fitted ellipse	Fitzibbon et al., 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 second derivative	Mery and Filbert, 2002
I, R, G, B	$K_1 \cdots K_3$	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[1] at 0ºand 90º	Mery and Filbert, 2002
I, R, G, B	Δ_Q	difference between maximum and minimum of BCLP[1]	Mery, 2003
I, R, G, B	Δ'_Q	$\ln(\Delta_Q + 1)$	Mery, 2003

I, R, G, B	σ_Q	standard deviation of BCLP[1]	Mery, 2003
I, R, G, B	Δ''_Q	Δ_Q normalized with average of the extreme of BCLP[1]	Mery, 2003
I, R, G, B	$\overline{Q}$	mean of BCLP[1]	Mery, 2003
I, R, G, B	$F_1 \cdots F_{15}$	first components of DFT of BCLP[1]	Mery, 2003
I, R, G, B	$\phi'_1 \cdots \phi'_7$	Hu moments with gray value information	Sonka et al., 1998
I, R, G, B	σ_g^2	local variance	Mery and Filbert 2002
I, R, G, B	Tx_d	mean (M) and range (Δ) of 14 texture features[2] with *d*=1,2,3,4,5.	Haralick et al., 1973
I, R, G, B	KL, DFT, DCT	64 first components of the KL, DFT, and DCT transform[3]	Castleman, 1996
L	L*a*b*	Color components of the region	Hunt,1991; Papadakis et al., 2000

[1]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).
[2]The following features are extracted based on a co-ocurrence matrix of the whole image of the potato chips: second 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.
[3]The transformation takes a re-sized window of 32 x 32 pixels which includes the middle of the potato chips.
[4]All mentioned features can be extracted using BALU Toolbox for Matlab (Mery, 2011).

4 APPLICATIONS

Segmentation is an essential step in computer vision and automatic pattern recognition process based on image analysis of foods as subsequent extracted data are highly dependent on the accuracy of this operation. If objects in image cannot be segmented correctly, it is difficult for object measurement, classification and recognition, hence impact interpreting and understanding that image (Brosnan and Sun, 2004). Segmentation can be achieved by three different techniques: thresholding, edge-based segmentation and region-based segmentation (Sonka et al 1999; Sun, 2000). Mery and Pedreschi (2005) developed a robust algorithm implemented in Matlab code (Mery, 2011) to segment potato chip images from a background (Figure 4). The proposed algorithm has three steps: (i) computation of a high contrast grey value image from an optimal linear combination of the RGB components; (ii) estimation of a global threshold using a statistical approach; (iii) morphological operation in order to fill the possible holes presented in the binary image.

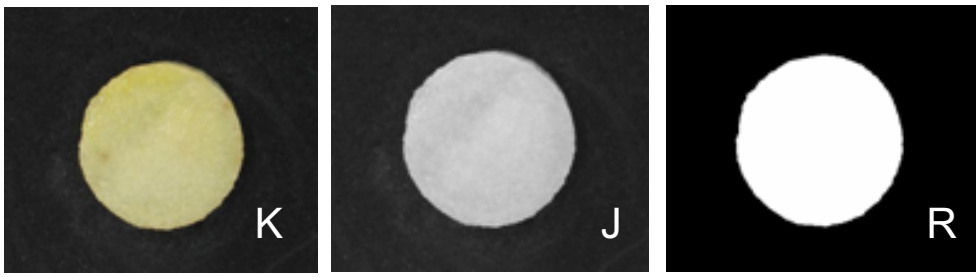


Figure 4. (K) Color image of a potato chip; (J) Grayscale image of the potato chip; (R) Segmented image of the potato chip. (Reprinted from *Food Research International*, available on line, Franco Pedreschi, Jorge León, Domingo Mery, Pedro Moyano). Development of a computer vision to measure the color of potato chips. Copyright 2006, by courtesy of Elsevier).

Pedreschi et al., (2004) implemented an approach to classify potato chips using pattern recognition from color digital images which consists of five steps: 1) image acquisition, 2) preprocessing, 3) segmentation, 4) feature extraction, and 5) classification. Ten chips prepared for each of the following six conditions were examined: two pre-treatments (blanched and unblanched) at three temperatures (120ºC, 150ºC and 180ºC). More than 1500 features were extracted from each of the sixty images. The feature selection was carried out based on the *Sequential Forward Selection* (SFS) method (Jain et al., 2000). Finally, eleven features were selected according to their classification attributes. Seven different classification cases (e.g. classification of the six classes or distinction between blanched and unblanched samples) were analyzed using the selected features. Although samples were highly heterogeneous, the correct classification of the potatoes chips using a simple classifier and a few number of features was possible obtaining a very good performance value in all cases (≥ 90%). These authors show how pattern recognition techniques could be easily and successfully applied to classify highly heterogeneous materials such as fried potato chips processed under different conditions. This methodology could be applied in food industry for automatic classification of other processed foods. On the other hand, Marique et al., (2003) used a pattern recognition methodology to classify fried potato chips with an artificial neuronal network. In the approach, grey level features of the apex, the center and the basal parts of each potato chip were obtained from a color image in order to assign each chip to one quality class according to color categories. Using a relatively small number of samples, the authors obtained a good agreement with human inspectors, yielding a classification performance around 90%.

The use of CV for color quality assessment of potato chips require an absolute color calibration technique based on a common interchange format for color data and a knowledge of which features from an image can be best correlated with product quality. With a digital camera it is possible to register the color of any

pixel of the image of the object using three-color sensors per pixel (Forsyth and Ponce, 2003). The most often used color model is the RGB model in which each sensor captures the intensity of the light in the red (*R*), green (*G*) or blue (*B*) spectrum respectively. Today the tendency is to digitally analyze the images of food items in order to firstly carry out a point analysis, encompassing a small group of pixels with the purpose of detecting small characteristics of the object, and secondly to carry out a global analysis of the object under study such as a color histogram in order to analyze the homogeneity of the object, (Du and Sun, 2004; Brosnan and Sun, 2004).

Pedreschi et al., (2006) design and implement an inexpensive computer vision system for measuring the color of a highly heterogeneous food material not only in shape as well in color such as potato chips in *L*a*b** units from RGB images (Figure 5). Given that RGB digital cameras obtain information in pixels, León et al. (2006) developed a computational color conversion procedure that allows the obtaining of digital images in L*a*b* color units for each pixel of the digital RGB image by testing five models: linear, quadratic, gamma, direct, and neural network. Additionally, a method is suggested for estimating the parameters of the models based on a minimization of the mean absolute error between the color measurements obtained by the models, and by a commercial colorimeter for uniform and homogenous surfaces. In the evaluation of the performance of the models, the neural network model stands out with an error of only 0.96%. Neural network architecture is shown in Figure 6. On the basis of the construction of these models, it is possible to find a L*a*b* color measuring system that is appropriate for an accurate, exacting and detailed characterization of potato chips, thus improving quality control and providing a highly useful tool for the food industry based on a color digital camera.

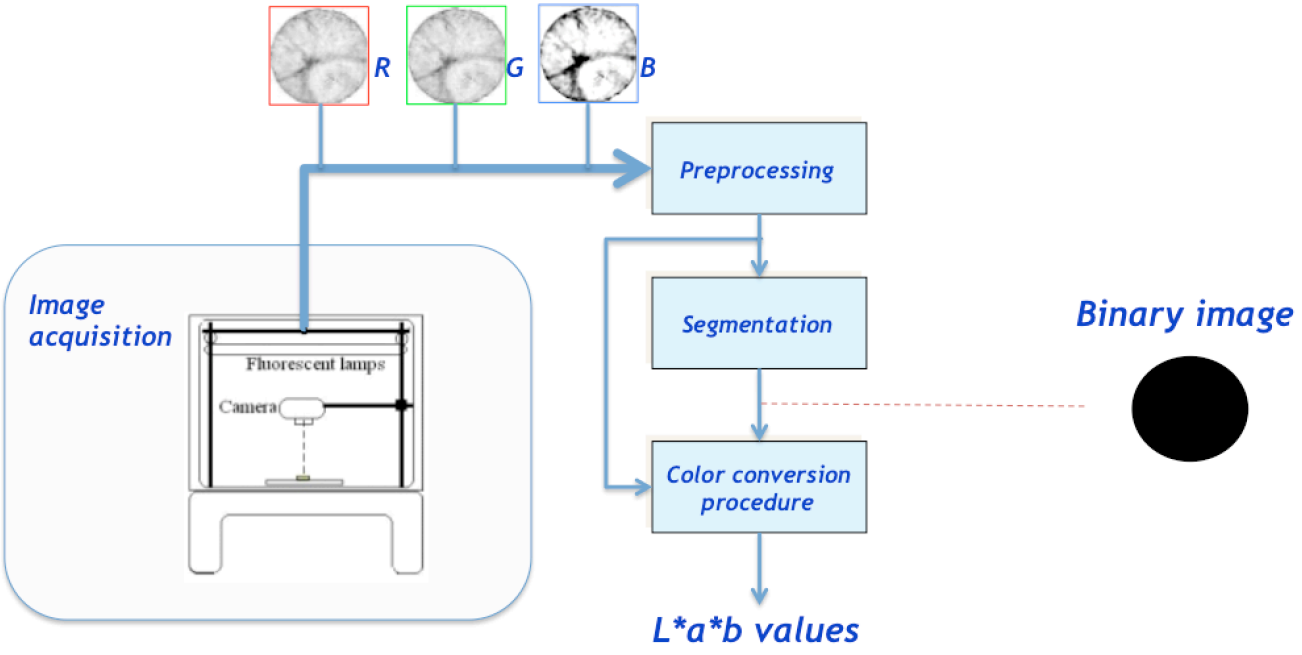


Figure 5. Schematic representation of the computer vision system used for color conversion process from RGB images to *L*a*b** units. (Adapted from *Food Research International*, available on line, Franco Pedreschi, Jorge León, Domingo Mery, Pedro Moyano). Development of a computer vision to measure the color of potato chips. Copyright 2006, by courtesy of Elsevier).

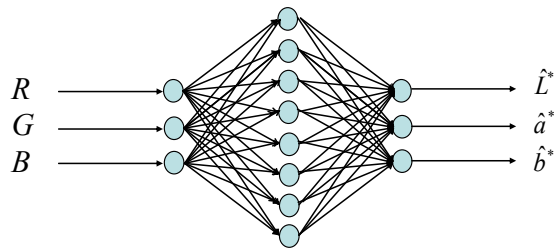
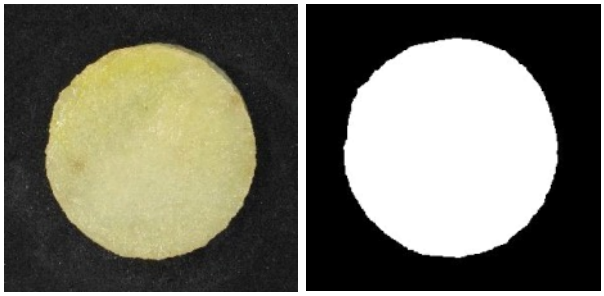


Figure 6. Architecture of the neural network used to estimate L*a*b* values from RGB images. (Reprinted from *Food Research International*, available on line, Katherine León, Domingo Mery, Franco Pedreschi, Jorge León). Color measurement in *L*a*b** units from RGB digital images. Copyright 2006, by courtesy of Elsevier).

In order to show the capability of the proposed method, León et al., (2006) measured the color of a potato chip using both a Hunter Lab colorimeter and their approach. The colorimeter measurement was obtained by averaging 12 measurements (in 12 different places of the surface of the chip), whereas the measurement using the digital color image was estimated by averaging all pixels of the surface image. The results are summarized in Figure 7 and the error calculated was only 1.8%.



(a) (b)

Instrument	L*	a*	b*
Hunter Lab	61.7	-1.7	26.6
Digital Image	66.9	-1.3	27.3

(c)

Figure 7. Estimate of L*a*b* values of a potato chip: a) RGB image; b) segmented image after Mery and Pedreschi (2005); c) L*a*b* measures using a commercial colorimeter and the approach of León et al., (2006). (Reprinted from *Food Research International*, available on line, Katherine León, Domingo Mery, Franco Pedreschi, Jorge León). Color measurement in *L*a*b** units from RGB digital images. Copyright 2006, by courtesy of Elsevier).

The kinetics of color changes in potato slices during frying at four temperatures was followed using the CVS implemented by Pedreschi et al. (2006). This CVS can be used to study as well foods different from potato chips by selecting their proper settings for image acquisition and digital image processing. Pedreschi et al., (2005) found a good linear correlation (R^2=0.9569) between acrylamide content of potato chips (moisture content ~ 1.8% in wet basis) and their color represented by the redness component *a** measured by CV in the range of the temperatures studied. Redness component *a** is an indicator of non-enzymatic browning; the lower *a** value, the paler the potato chip (Figure 8). As the frying temperature increase from 120 to 180 °C, the resultant chips get more red and darker as a result of non-enzymatic browning reactions that are highly dependant on oil temperature. Blanching reduces the *a** value of potato chips due to the leaching out of reducing sugars previous to frying inhibiting in this way non-enzymatic browning reactions and leading to lighter and less red chips. Figure 9 shows visually how the potato chips get more red and darker as the frying temperature increased from 120 to 180 °C. Besides, at the same frying temperature, blanching pre-treatment lead to paler potato chips after frying.

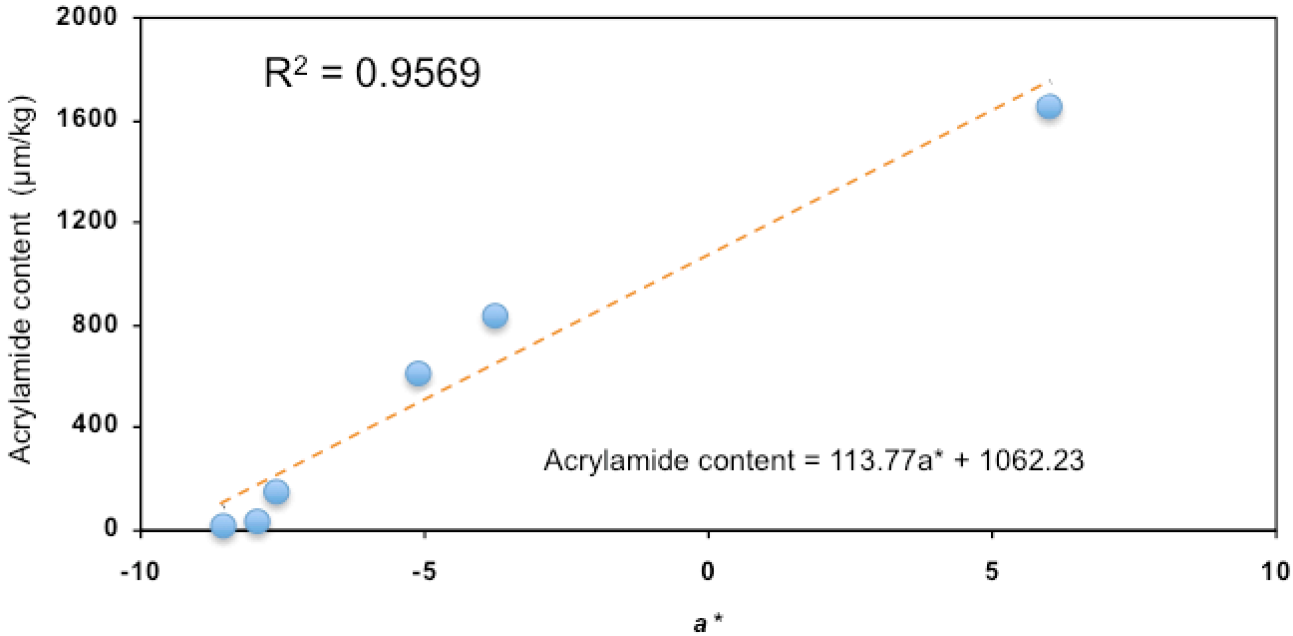


Figure 8. Acrylamide content *vs.* color parameter *a** for control and blanched potato chips (moisture content of ~1.8% -wet basis-) fried at 120, 150 and 180 °C. (Reprinted from *Food Research International*, 38, Franco Pedreschi, Pedro Moyano, Karl Kaack, Kit Granby). Color changes and acrylamide formation in fried potato slices. Pages 1-9, Copyright 2005, by courtesy of Elsevier).

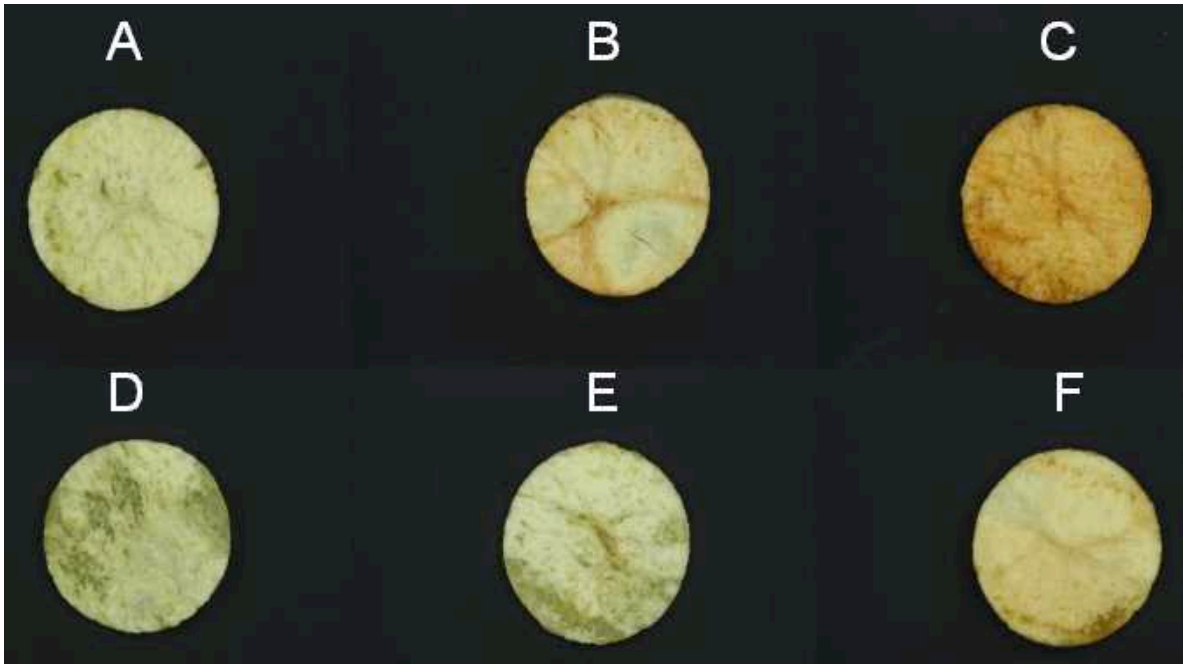


Figure 9. Images of potato chips (moisture content of ~1.8% -wet basis-): A) Control fried at 120 °C; B) Control fried at 150 °C; C) Control fried at 180 °C; D) Blanched fried at 120 °C; E) Blanched fried at 150 °C; F) Blanched fried at 180 °C. Control are unblanched slices. Blanching treatment was in hot water at 85 °C per 3.5 min. (Reprinted from *Food Research International*, 38, Franco Pedreschi, Pedro Moyano, Karl Kaack, Kit Granby). Color changes and acrylamide formation in fried potato slices. Pages 1-9, Copyright 2005, by courtesy of Elsevier).

Mendoza et al (2007) evaluated images of commercial potato chips were evaluated for various color and textural features to characterize and classify the appearance and to model the quality preferences of a group of consumers. Features derived from the image texture contained better information than color features to discriminate both the quality categories of chips and consumers' preferences. A stepwise logistic regression model was able to explain 86.2% of the preferences variability when classified into acceptable and non-acceptable chips.

Pedreschi et al., (2010) classify automatically 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.

Gokmen and Mogol (2010) develop a computer vision-based image analysis algorithm using color segmentation for the prediction of acrylamide level in thermally processed foods. Obtained digital images were analyzed using a semiautomatic segmentation algorithm to calculate the browning ratio of potato crisps and the calculated browning ratio were successfully correlated with acrylamide level of potato chips. So, it was possible to predict the levels of acrylamide in test samples by means of their browning ratio values. The image analysis technique described here can be used as an online process control tool for frying industry.

On-line Near infrared spectroscopy (NIR) interactance based methodology was found to predict fat and dry matter of potato chips with high accuracy, i.e. prediction errors of 0.99 and 0.86% (w/w), respectively (Pedreschi et al., 2010). The corresponding correlations between predicted values and reference values were 0.99 and 0.97 for fat and dry matter. For acrylamide an average prediction error of 266 μg/kg was achieved using NIR interactance and VIS reflectance signals in combination. The correlation between predicted values and reference values was 0.83 for this model. The acrylamide prediction error is fairly high, and indicates that the system should be used for screening or classification rather than prediction. The system may well be used to separate samples with very high acrylamide contents from samples with average to low contents.

Pedreschi et al., (2012) defined potato chip quality categories for different processing conditions by using a selected sensory panel only in analyzing surface color together with the help of a survey applied to potato chip consumers to define color acceptability. Potato chips with a pale color do not have the rich smell expected by the consumers. Indeed, more than 80% of panelists rejected the product. For more than 60% of consumers, potato chips must be a bit toasted with a color golden brown but not burned. Besides, reliable models were obtained to correlate oil temperature–frying time combination required to get the most preferred color by consumers with the different pre-treatments tested. It was observed that the shorter times and lowest oil temperatures correspond to the pre-treatment blanching plus drying, which could mean considerable energy saving during potato slice frying.

5 FRIED POTATO SORTING

Different problems involving vision are associated with frying potato pieces (either slices or strips). One is the presence of defects such as black dots, necrosis, etc. It involves on-line screening and eventual rejection of every chip (Marique et al., 2003). Another is the development of a dark coloration because of Maillard reaction between reducing sugars and amino groups (Márquez and Añón, 1986). This must be assessed at the laboratory on a sample from any potato batch intended for processing, because tubers can look perfectly fine and however develop a too intensive or heterogeneous browning, or dark tips, thus leading to consumer rejection. Defective batches are refused, at the producer prejudice.

Browning evaluation must also be performed frequently at the laboratory on chips samples taken from the frying lines, thus allowing to pilot the process. Finally, there is the synthesis of acrylamide during frying,

due to reaction of asparagine and reducing sugars (Pedreschi et al., 2005). As this reaction pathway is clearly correlated to Maillard's reactions (Mottram and Wedzicha, 2002; Stadler et al., 2002; Pedreschi at al., 2005), it has been proposed by several authors to perform quick and easy measurement by way of image analysis of chips browning, rather than using painstaking chromatographic methods. Acrylamide is suspected to be a molecule with significant toxicological effects, namely carcinogenic, neurotoxic and mutagenic (Rosen and Hellenäs, 2002). We shall describe several approaches recently developed by several teams to cope with automation of image analysis in this field.

Browning sorting using Artificial Neural Networks (ANN) by CARAH (Centre pour l'agronomie et l'agro-industrie de la province de Hainaut, Belgium).

To visually estimate chips darkening at frying, one performs a simple frying assay during 3 minutes at 180°C on 20 chips issued from the central part of 20 different potatoes. Each stick is then assigned a category by visual examination under standard white light. The jury builds its evaluation with the help of a standard reference card (Figure 10), judging both from overall darkening of the stick and from contrast between the extremities (apex and base) and the center of the stick. Heterogeneous coloration is also given a penalty.

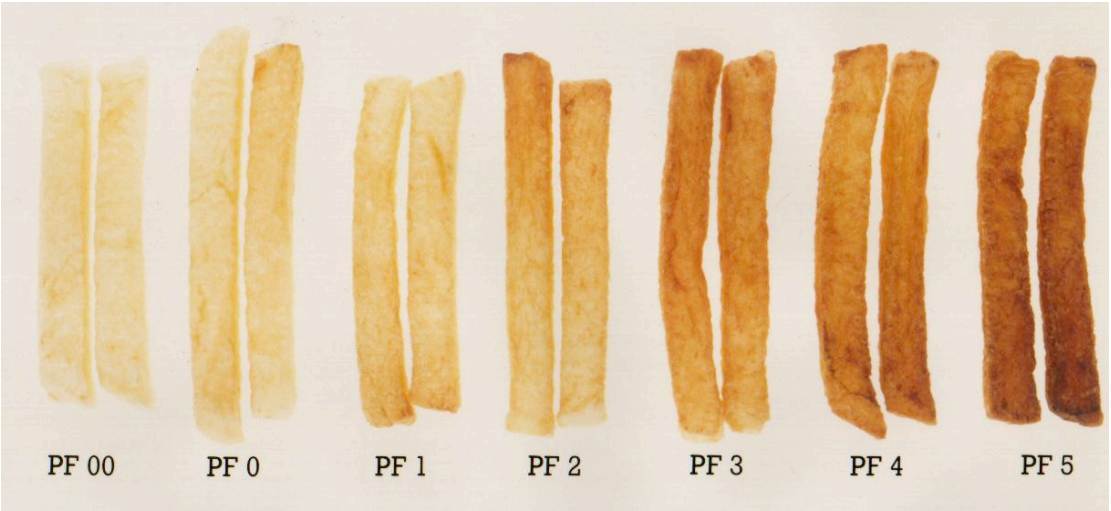


Figure 10. Potato piece reading card for browning categories.

There are of course some problems associated with this subjective procedure. In particular, estimations may vary with the jury. Even for a given jury, sample variability can influence results, since narrow distributions would tend to be spread over the scale. It is thus of great interest to develop a model that would allow reproducible estimation of chips color category (Marique et al., 2003).

Artificial Neural Networks (ANNs) attain very good performance when used to predict values for complex non-linear systems (Mittal and Zhang, 2000; Wilkinson and Yuksel, 1997). Moreover, they are endowed with broad capacities of generalization so that they can give useful information for cases that were not part of their training set (Schalkoff, 1997; Wilkinson and Yuksel, 1997; Marique and Wérenne, 2001; Yang et al., 2002). They appear to be logical choice provide successful prediction of darkening index for fried potatoes. Image analysis was used to extract gray levels intensities from an image data bank gathered from routine frying assays of 12 different mealy potato cultivars (*Annabelle, Bintje,*

Cantate, Charmante, Cyclone, Daisy, Farmer, Innovator, Lady Olympia, Liseta, Markies, Victoria). Three values were computed for each chip, corresponding to the mean gray values at the apex, center and base of the chip respectively (Marique et al., 2003). The ANN consisted of feed-forward back-propagation with a hidden layer of 4 neurons with sigmoid transfer functions, and bias (Figure 11). The output layer consisted of a single linear neuron with bias that issued the estimated value of the color category (from 0 to 4).

The ANN was trained with a Lenvenberg-Marquardt algorithm (Schalkoff, 1997) and the output values were compared to the corresponding color categories estimated by human operators who assigned every chip to a color category, ranging from 0 (very pale) to 4 (very dark). The jury was instructed first to score a chip on the basis of its global appearance, then to put it in the category immediately superior should it possess clearly contrasted dark ends (i.e. more then 1 cm long).

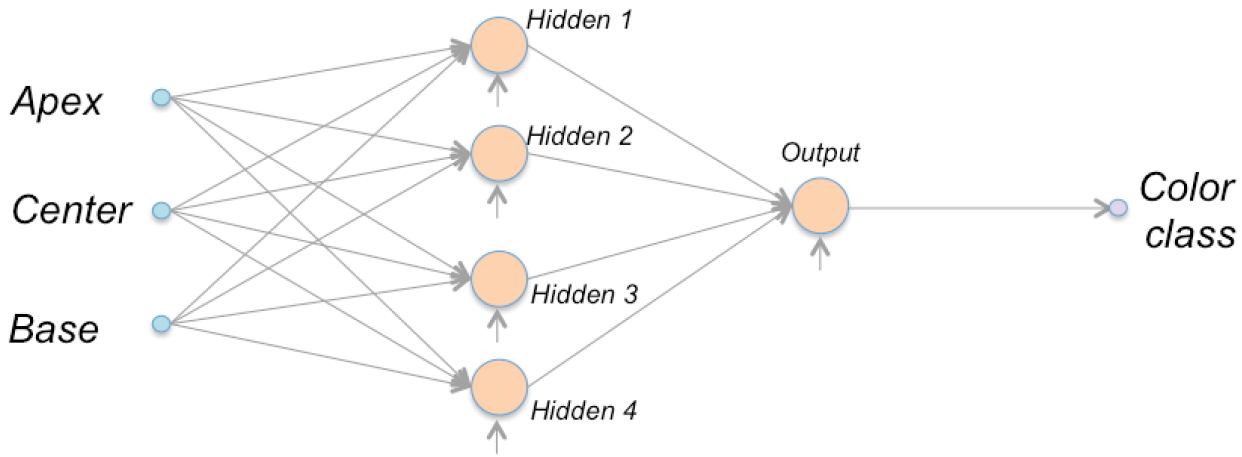


Figure 11. Structure of a two layers feed-forward ANN with 3 inputs, 4 hidden neurons with bias and one output neuron with bias. (Adapted from *Journal of Foood Science*, Vol. 68, T. Marique, A. kharoubi, P. Bauffe, C. Ducattillon). Modeling of fried potato chips color classification using image analysis and artificial neural network. Pages 2263-2266, Copyright 2003, by courtesy of Institute of Food Technologists).

Figure 12 allows understanding the way the jury assigns a particular color value to any chip. The different color categories are distributed throughout the gray values scale, following one another with partial overlapping. This comes from the fact that when a particular chip stands exactly between two categories, the jury will select one at random, and so either undervalue or overvalue it, hence the overlapping.

Chips are assigned to category 0 if they appear both very pale (gray levels over 150) and rather paler at the extremities than in the center (population laying at the right side of the diagonal, Figure 3). A chip will be assigned to category 1 either if it appears clearer in the center but possess contrasted dark ends or if it appears clearly darker in the center, with pale ends. Category 1 is thus clearly split in two subpopulations (ellipsoids in Figure 12) flanking both sides of category 0. Categories 2, 3 and 4 then progressively regroup darker chips, generally clearly pale in the center with more or less contrasted dark

ends. Thus, it is only for the two lower color categories that the jury will overvalue a stick possessing dark contrasted extremities. For higher color categories, estimation are based mostly on the chip global (center) appearance, dark contrasted ends being considered as "normal" (Marique et al., 2003).

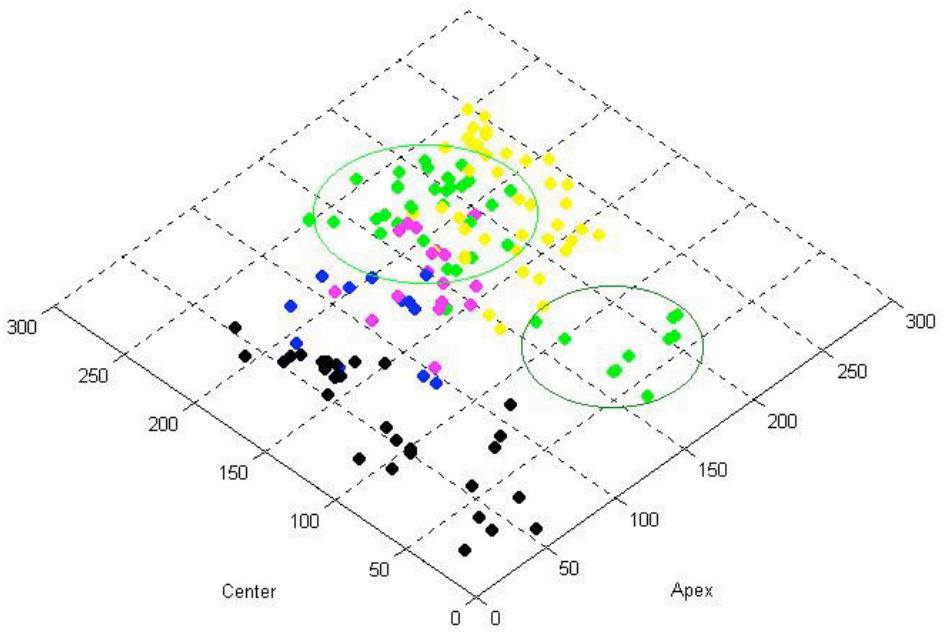


Figure 12. Mean gray values for the center and the apex of the chips. The color code indicates the class of color. Yellow: 0; green: 1; magenta: 2; blue: 3; black: 4. The ellipsoids contain the two sub-populations of class 1: in dark green, globally darker sticks; in light green, paler sticks with contrasted dark ends. (Reprinted from *Journal of Foood Science*, Vol. 68, T. Marique, A. kharoubi, P. Bauffe, C. Ducattillon). Modeling of fried potato chips color classification using image analysis and artificial neural network. Pages 2263-2266, Copyright 2003, by courtesy of Institute of Food Technologists).

The ANN showed good performance, with correlation coefficients of 0.972 for training data and of 0.899 for validation data. The trained ANN was used to generate a complete set of predictions for the different possible combinations of gray levels of the center and of the apex of the chips. This is illustrated in Figure 13, where computing was performed using equal gray values for both the base and the apex of the chips. The network displays a complex and continuous behavior for the low color categories 0, 1 and 3 but operates a discrete classification between categories 3 and 4 only. This could be a consequence of both the greatest number of data points for high color categories and of the more complex behavior of the jury for low color categories (Marique et al., 2003).

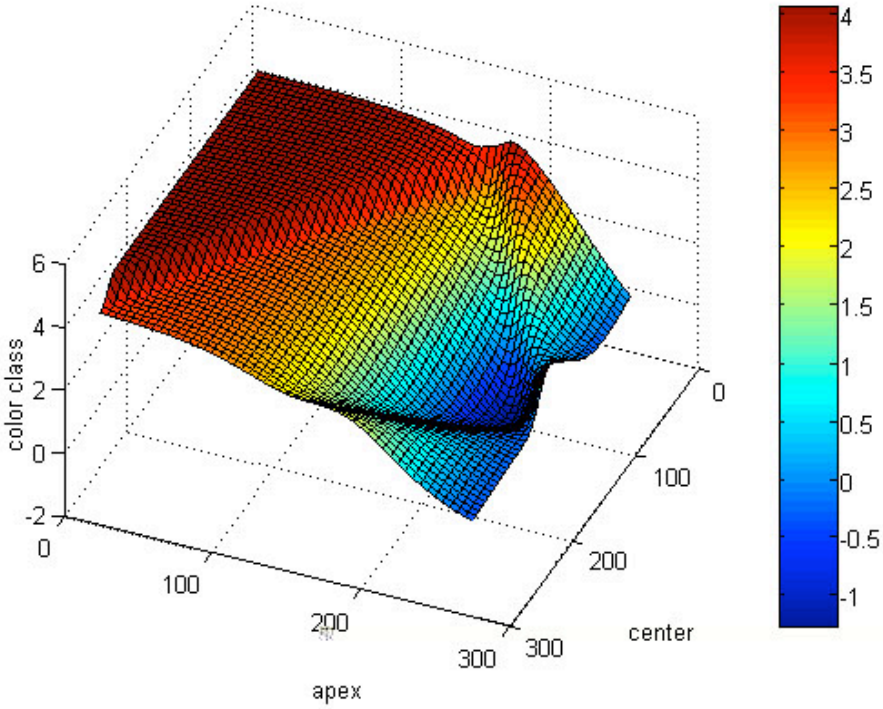


Figure 13. Response of the ANN: color class categories as a function of all possible combinations of gray levels of the center and the apex of the chips. (Reprinted from *Journal of Foood Science*, Vol. 68, T. Marique, A. kharoubi, P. Bauffe, C. Ducattillon). Modeling of fried potato chips color classification using image analysis and artificial neural network. Pages 2263-2266, Copyright 2003, by courtesy of Institute of Food Technologists).

A more complete simulation is shown in Figure 14, illustrating the discrete color categories (the values predicted from the ANN have been rounded to the nearest integer) obtained for all the possible combinations of gray levels of the three regions of the chips. Again, a more complex behavior is observed for low values color categories. Intermediate categories 2, 3 and 4 also extend between two “wings”, either globally paler with dark ends or globally darker with pale ends. Color classification varies most with apex and center gray values (Marique et al., 2003).

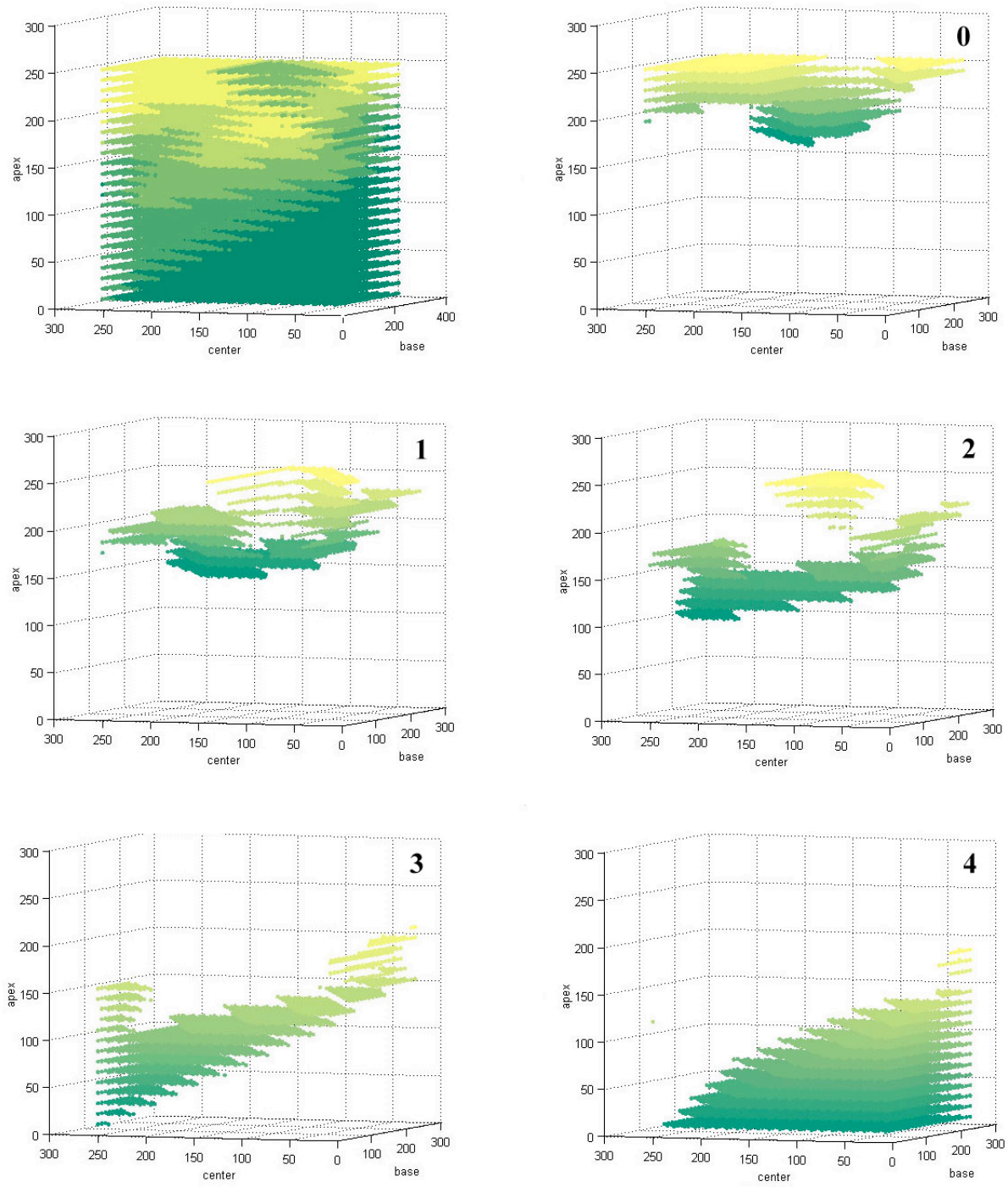


Figure 14. Discrete color categories obtained for all the possible combinations of gray levels for the three regions of the chips. Upper left: general presentation. Others: partial views of each color category, from 4 (upper right) to 0 (bottom right). (Reprinted from *Journal of Foood Science*, Vol. 68, T. Marique, A. kharoubi, P. Bauffe, C. Ducattillon). Modeling of fried potato chips color classification using image analysis and artificial neural network. Pages 2263-2266, Copyright 2003, by courtesy of Institute of Food Technologists).

Browning sorting without ANN (Walloon Agricultural Research Center, Belgium).

This research center affiliated to Gembloux Agricultural University in Belgium developed a home-made system for quality evaluation of French fries (Figure 15).

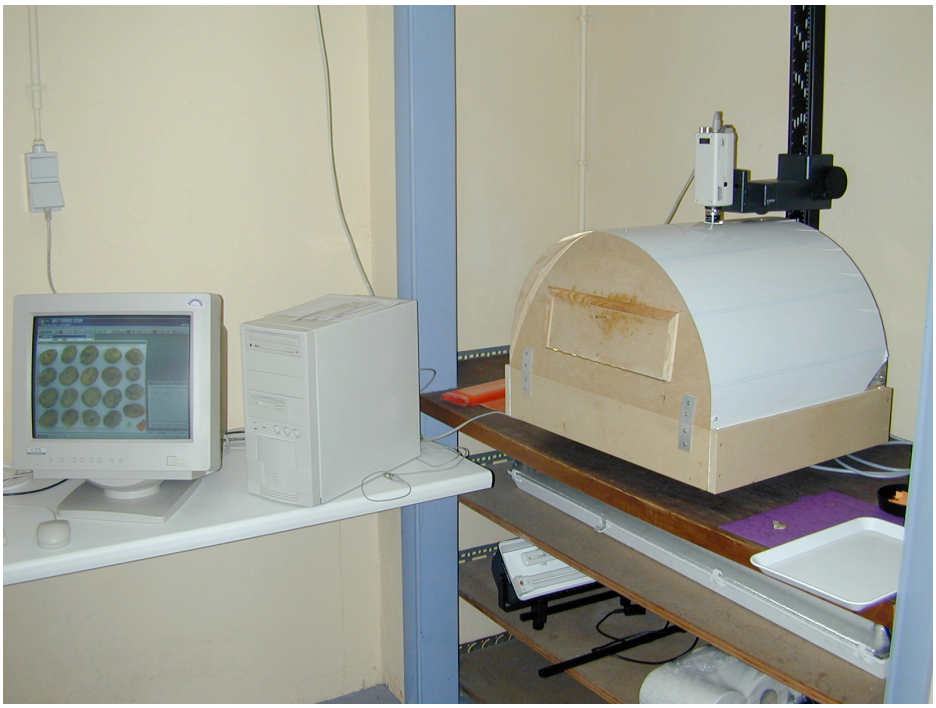


Figure 15. Device for French fry quality evaluation (Gembloux Agricultural University in Belgium).

Here, 20 French fries are cooked and then arranged on a tray with a reference tongue (see Figure 16). The reference tongue is directly extracted from the USDA reference card in order to represent the 7 reference colors on each sample: for each shooting, a tray contains 20 French fries and a reference tongue. The tray is then placed in the box and an image is taken.

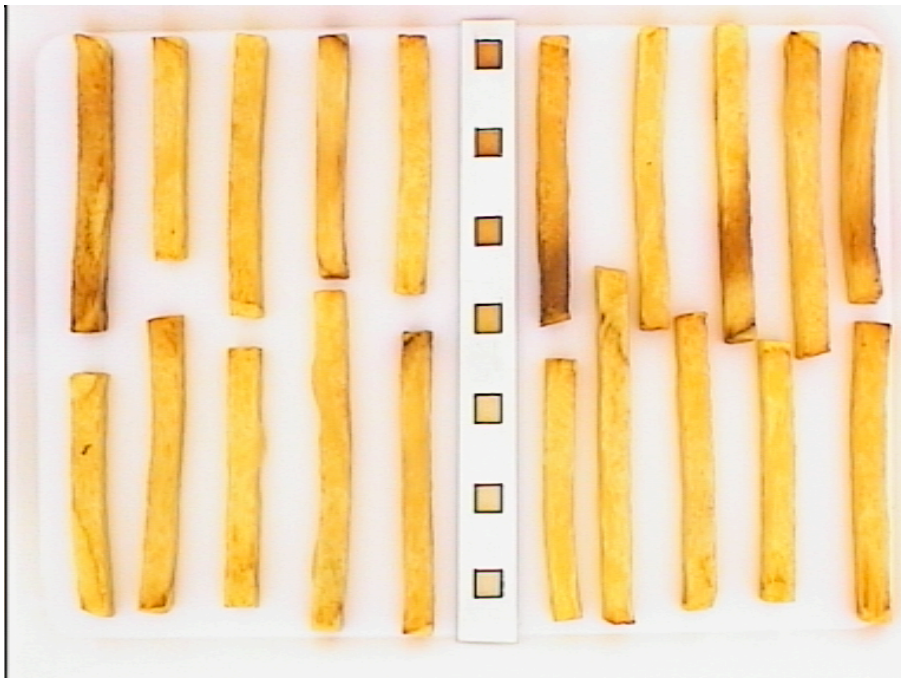


Figure 16. Tray ready for image analysis with 20 French fries and 7 colored squares

Image analysis is done using Image Pro Plus software (Media Cybernetics). This general software is foreseen for very various applications. The image analysis scheme is the following one: after the opening of the program, a choice must be done between the analysis of an already archived image or a new one. Then the program checks the number of references, represented by the 7 little colored squares arranged on each tray and offers a manual correction in case where this number is different from 7. The references are then scanned. French fries are scanned and counted too and the program offers again a manual correction if the number of French fries is different from 20. Once these checkings are done, macros sequences successively comply in a few seconds (via sending data to Excel) to compare colors of the French fries with the reference tongue and to determine the color parameters. For this comparison, RGB images are first converted into grey scale and then, their luminous intensity is estimated by Image Pro Plus. All these stages are carried out in a friendly environment until the automatic redaction of a detailed (containing photography of the sample, the date, the color parameters etc.) and archived report.

The image analysis method must be compared to the sensory analysis (visual comparison). That's why we analyze a first series of 100 samples with both methods. The correlation is up to 0.9510 between the reference analysis and the new technique, it is a very good result compared with the weak repeatability of the reference method, submitted to the judgment of colors by human eye (Figure 17).

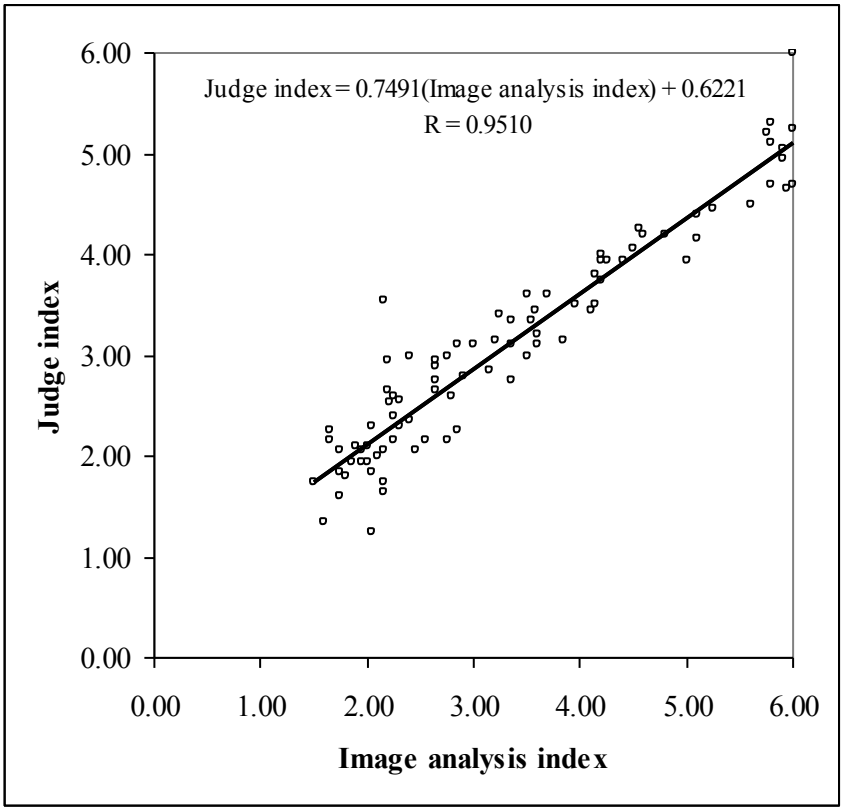


Figure 17. Correlation between the visual measurement and the measurement by image analysis

Browning sorting and acrylamide estimation using ANN by CARAH

Acrylamide concentration determination nowadays appears to be a necessity since very high concentrations of this potentially toxic molecule were detected in amylaceous fried foodstuffs (Rosen and Hellenäs, 2002). However, standard procedures for acrylamide determination involve slow and expensive methods of chromatography and mass spectroscopy and, thus cannot be used for routine analysis. It was therefore a logical step to develop alternative methods based on image analysis of chips browning to measure acrylamide concentration. One could expect good correlation between non-enzymatic browning development and acrylamide formation, since several studies reported excellent linear relationships between browning and acrylamide accumulation in chips and in model systems (Pedreschi et al., 2005 Mottram and Wedzicha, 2002; Stadler et al., 2002).

CARAH and an Belgian industrial partner (Rovi-Tech s.a.) developed an high speed imaging system coupled with ANN computing which consists in a fully automatic device that takes a snapshot of every chips tested, then issues results for both color category and acrylamide concentration (Figure 18). The system is intended for analysis of incoming potato batches as well as for checking pre-fried chips for quality control in food distribution. The heart of the system is Rovi-Tech's ILB-25 (Image Learning Box), a very efficient ANN technology that allows easy and powerful correlations for complex visual data analysis.

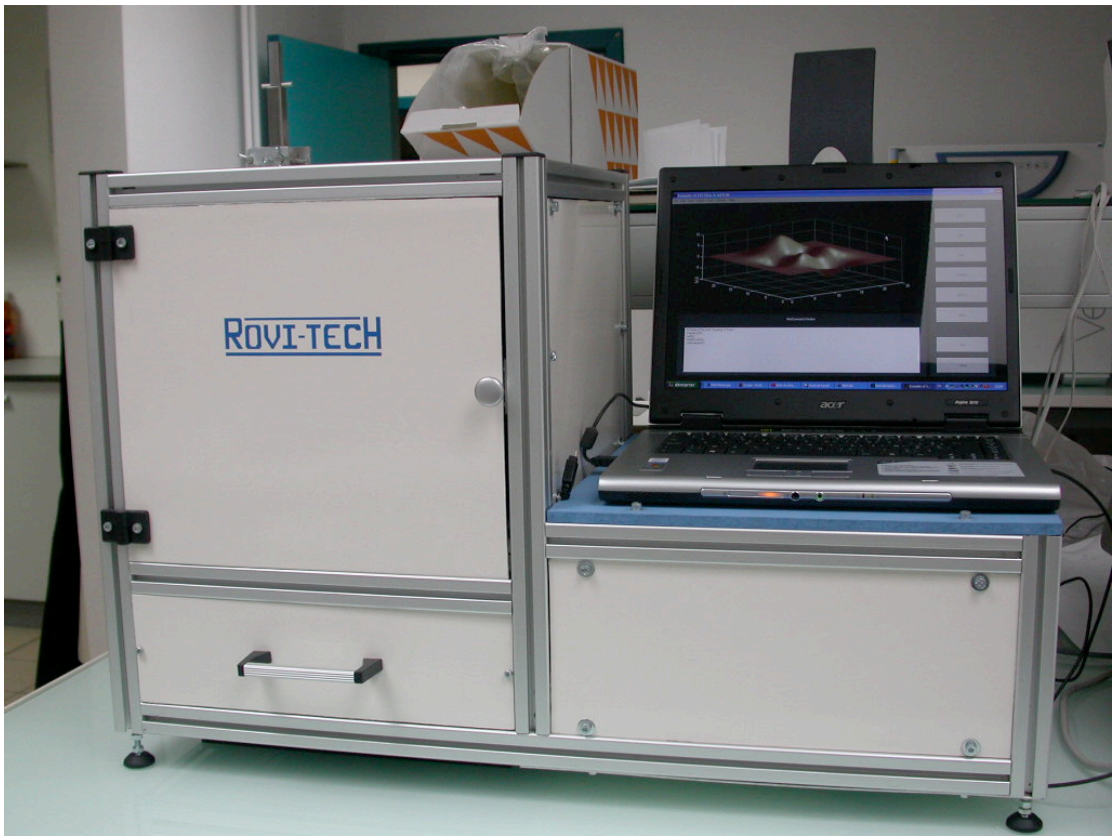


Figure 18. ANN imaging system for determination of color class and acrylamide concentration in chips

6 CONCLUSIONS

Grayscale and color images of potato chips are useful to extract high performance features for an appropriate classification. The most relevant features for potato chip classification were either texture features or *L*a*b** features. There was no geometric feature proper for classification of the potato chips since their values did not change significantly for the different conditions employed by Pedreschi et al., (2004). Potato chips were properly classified obtaining very good values despite its high heterogeneity. Some features extracted from 2D potato chip 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 texture information in 2D images. The automatic classification methodology presented for potato chips is general and has a wide range of potential uses. It could be interestingly applied this methodology 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 implemented CVS by Pedreschi et al., (2006) allows determining the color of potato slices from RGB images into *L*a*b** units in an easy, precise, representative, objective and inexpensive way. This was achieved by integrating previously developed routines for image pre-processing, segmentation and

color conversion into one computational program to make easier and faster the color measuring of potato chips in *L*a*b** units. The CVS allows easy measurements of the color over the entire surface of a potato chip or over a small specific surface region of interest.

León et al. (2006) developed a tool for high resolution L*a*b* color measurement. This system of color measurement is very useful in the food industry because a large amount of information can now be obtained from measurements at the pixel level which allows a better characterization of foods and thus improves quality control. Five models were built that are able to measure color by CV in potato chips in L*a*b* units and simultaneously measure the color of each pixel on the target surface (this is not the case with conventional colorimeters). The best results were achieved with the quadratic and neural network model, both of which show small errors (close to 1%). With respect to the neural network it was demonstrated that with a correct selection of parameters and good architecture it is possible to solve problems such as the one addressed in this work.

Gokmen and Mogol (2010) showed that the browning ratio may be considered as a reliable indicator of acrylamide concentration fried potatoes since its calculation is simply based on the predefined color references. This technique can be effectively used as a process control tool to monitor the browning ratio for product safety evaluation purposes. On the hand, Near infrared spectroscopy (NIR) is was used to investigate the possibilities of using on-line NIR monitoring of acrylamide, moisture and oil content in potato chips (Pedreschi et al., 2010).The acrylamide prediction error is fairly high, and indicates that the system should be used for screening or classification rather than prediction. The system may well be used to separate samples with very high acrylamide contents from samples with average to low contents.

7 ACKNOWLEGDMENTS

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