Quality Evaluation and Control of Potato Chips and French Fries

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1 Introduction

Potato chips have been popular salty snacks for 150 years, and retail sales in the US are worth about \$6 billion/year, representing 33 percent of the total sales of this market (Garayo and Moreira, 2002; Clark, 2003). In 2001 about 50 percent of the US potato crop was processed to produce 11 300 million kg of processed potatoes, of which 21.6 percent were made into chips. The worldwide trade over recent years indicates that about 7.4×10^7 kg of potato chips were exported, with a value of ∼\$165 million annually (Economic Research Service, 2004).

Frying in hot oil at temperatures between 160° and 180°C is characterized by very high drying velocities, which are critical to improve not only the mechanical but also the structural properties of the potato chips (Baumann and Escher, 1995). Potato chips are thin slices whose moisture content decreases from around 80 percent to almost 2 percent when they are fried. However, the drying in oil inevitably leads to a considerable oil uptake of around 35 percent, most of which is located on the surface of the chip (there is almost no penetration during frying) and adheres to the surface at the end of frying. Therefore, a high proportion of oil penetrates into the food microstructure during the post-frying cooling stage (Ufheil and Escher, 1996; Aguilera and Gloria, 2000; Bouchon *et al*., 2003).

In the potato chip industry, the quality of each batch of potato tubers must be tested before processing, and of the various quality criteria the visual aspect, especially the

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color, is of great importance (Marique *et al*., 2005). Color of potato chips is the first quality parameter evaluated by consumers, and is critical in the acceptance of the product (Pedreschi *et al*., 2006). Consumers tend to associate color with flavor, safety, storage time, nutrition, and level of satisfaction, due to the fact that color correlates well with physical, chemical, and sensorial evaluations of food quality. The color of potato chips changes during frying, as the components of potatoes are restructured. Consequently, the surface color reflects not only the heterogeneous surface formed as a result of frying but also the non-homogeneous oil distribution. Visual aspects, such as surface color and appearance, can be studied using computer vision techniques in order to determine the potato chip.

Acrylamide, which is formed in potatoes during frying and is highly related to the color of potato chips, is suspected to have critical implications for human health, since it has recently been found to be a carcinogen in rats (Mottram and Wedzicha, 2002; Rosen and Hellenäs, 2002; Stadler *et al*., 2002; Pedreschi *et al*., 2005). Potato chip color is affected by the Maillard reaction, which depends on the content of reducing sugars, amino acids, or proteins at the surface. It is also affected by the frying temperature and time (Márquez and Añón, 1986). Generally, potato tubers that contain more than 2 percent of reducing sugars are discarded for frying, since they generate too dark a coloration. Research has demonstrated that 2.5–3 mg of reducing sugar per gram of potatoes should be the maximum value accepted for potato chip preparation (Lisinska and Leszczynski, 1989).

In European factories, some computer vision systems are used for the on-line evaluation of potato chips, allowing chips to be sorted according to defects such as black spots or blisters (Marique *et al*., 2005). Some researchers have been also working on a promising device that is able both to classify chips according to color and to predict acrylamide levels using neural networks (Marique *et al*., 2003, 2005), and some are currently evaluating devices based on this system with the expectation that it will be fully operational very soon. Apart from the neural network, there is another device based on statistical pattern recognition for color classification of potato chips (Marique *et al*., 2003; Pedreschi *et al*., 2004). Researchers in this topic are routinely providing classical visual evaluation against a standard chart, and have conducted a good amount of work to testify which criteria (overall appearance, heterogeneity, contrasted extremities, etc.) should be taken into account by the operator to evaluate the surface of potato chips. In this chapter, the application of computer vision to study the quality attributes of potato chips is summarized.

2 Computer vision

Computer vision (CV) is a novel technology for acquiring and analyzing an image in order to obtain information or to control processes. Basically, a computer vision system (CVS) consists of a video camera for image acquisition, illuminants with standard settings, and computer software for image analysis (Papadakis *et al*., 2000; Brosnan and Sun, 2004). Image processing and image analysis are at the core of CV, with numerous

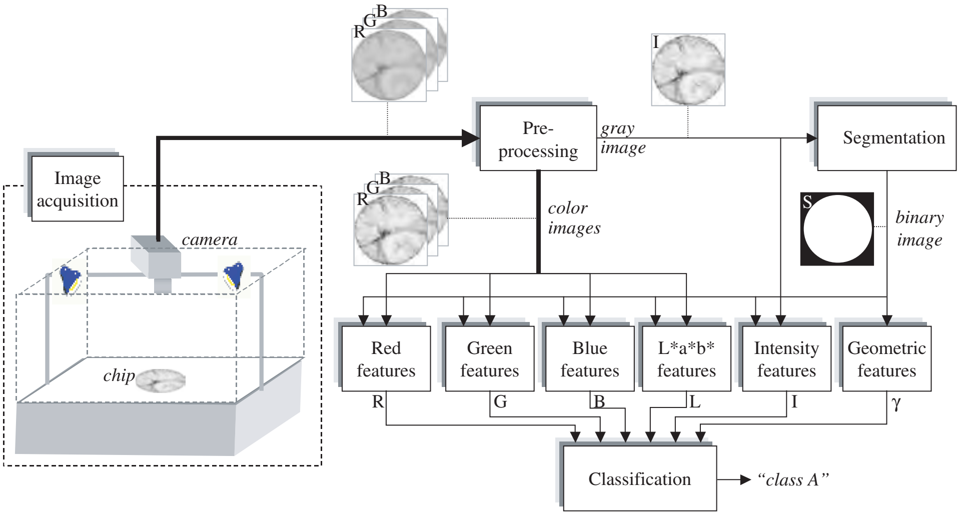


Figure 22.1 Schematic representation of the pattern-recognition process required for automatic classification of potato chips. (Reprinted from Pedreschi *et al.*, 2004©, by courtesy of the Institute of Food Technologists.)

algorithms and methods being capable of objectively measuring and assessing the appearance quality of agricultural products (Sun, 2004). Figure 22.1 shows a schematic representation of a general CV pattern-recognition process required for the automatic classification of potato chips, which involves the following four steps (Castleman, 1996; Mery *et al.*, 2003): image acquisition, image pre-processing and segmentation, feature extraction, and classification.

2.1 Image acquisition

A digital image of the potato chip is captured and stored in the computer. When acquiring images, it is important to consider the effect of illumination intensity and the orientation of specimens 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 an image of which each pixel is associated with three digital values as red (R), green (G), and blue (B). Figure 22.2 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:

1. A color digital camera with 4 megapixels of resolution (Power Shot A70, Canon, Tokyo, Japan)
2. Four natural daylight 18-W fluorescent lights (60 cm in length) with a color temperature of 6500 K (Philips, Natural Daylight, 18 W) and a color index (Ra) close to 95 percent for proper illumination
3. A wooden box where the illuminating tubes and the camera are placed; the interior walls of the box are painted black to minimize background light.

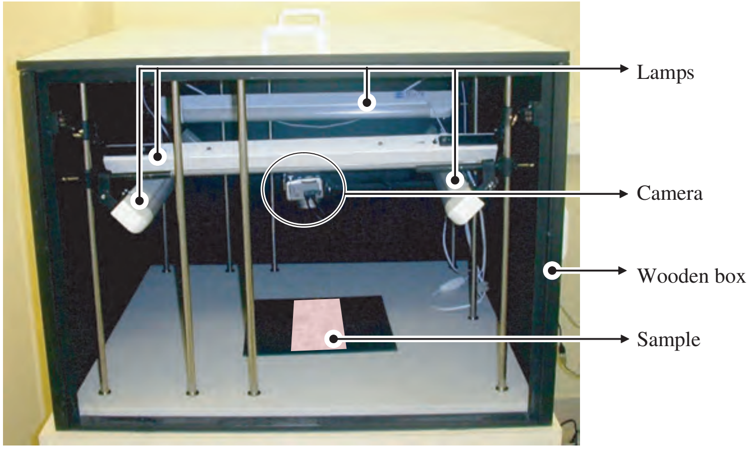


Figure 22.2 Image-acquisition system developed to evaluate potato chip quality. (Reprinted from León *et al.*, 2006©, courtesy of Elsevier.)

2.2 Image pre-processing and segmentation

The digital images taken must be pre-processed to improve their quality before they are analyzed. Using digital filtering, the noise in the image can be removed and the contrast enhanced. Sometimes in this step the color image is converted to a gray-scale image, called the intensity image (I). The intensity is used to divide the images into disjointed regions with the purpose of separating the region of interest from the background. This segmented image (S) is a binary image, where 0 (black) and 1 (white) indicate background and object, respectively. In our case, such a region of interest corresponds to the area where the potato chip is located for the test.

Segmentation is an essential step in computer vision, and the accuracy of this operation is critical in automatic pattern recognition for food image analysis. This is because pattern recognition is based on the data subsequently extracted from the segmentation process (Brosnan and Sun, 2004). Segmentation detects regions of interest inside the image, or structural features of the object, and can be achieved by three different techniques: thresholding, edge-based, and region-based (Sonka *et al.*, 1998; Sun, 2000) segmentation. Mery and Pedreschi (2005) developed a robust algorithm implemented in Matlab 6.1 software (The MathWorks, Inc., Natick, Mass., USA.) to segment potato chips from the background. The segmentation has three steps:

1. Computation of a high-contrast gray-value image from an optimal linear combination of the RGB components
2. Estimation of a global threshold using a statistical approach
3. A morphological operation in order to fill the possible holes presented in the binary image (Figure 22.3).

2.3 Feature extraction

Image feature extraction is one of the most active research topics in computer vision (Du and Sun, 2004). Following segmentation, feature extraction is concentrated principally

Figure 22.3 Potato images: (a) color image of a potato chip; (b) gray-scale image of (a); (c) segmented image of (a). (Reprinted from Pedreschi *et al.*, 2006©, by courtesy of Elsevier.)

around the measurement of the geometric properties (size and shape) and surface characteristics of regions (color and texture) (Zheng *et al.*, 2006). It is important to know in advance which features provide relevant information for the classification. In order to reduce the computational time required in the pattern-recognition process, it is necessary to select the features that are relevant for the classification. For this reason, feature selection must be performed in a training phase.

Features extracted from potato chip images by Pedreschi *et al*. (2004) are described in Table 22.1, and are grouped into six types:

1. Geometric (γ)
2. Intensity (gray-scale image) (I)
3. Red component (R)
4. Green component (G)
5. Blue component (B)
6. Mean values of the L*a*b* components (L).

The details regarding now these features are calculated can be found in the references cited in Table 22.1.

2.4 Classification

The extracted features of each region are analyzed and assigned to one of the defined classes. A classifier is designed following supervised training. Simple classifiers can be implemented by comparing the measured features with threshold values. However, it is also possible to use more sophisticated classification techniques, such as statistical and geometric analyses, neural networks, and fuzzy logic (Castleman, 1996; Jain *et al.*, 2000; Mery *et al.*, 2003). For example, in statistical pattern recognition, classification is performed using the concept of similarity – i.e. patterns that are similar are assigned to the same class (Jain *et al.*, 2000). In other words, a sample is classified as class “i” if its features are located within the decision boundaries of class “I”. Furthermore, a decision-tree classifier can be implemented to search for the feature that can separate one class from the other classes with the most confidence (Safavian and Landgebe, 1991).

Table 22.1 Extracted features from images of potato.

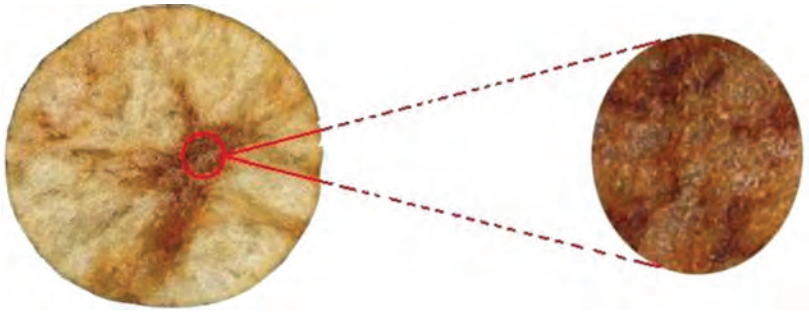
Type	Feature	Description	Reference
γ	$(\bar{i}, \bar{j})$	Center of gravity	Castleman, 1996
γ	h, w, A, L, R	Height, width, area, roundness, and perimeter	Castleman, 1996
γ	$\phi_1 \ldots \phi_7$	Hu's moments	Sonka *et al.*, 1998
γ	$\lvert DF_0 \rvert \ldots \lvert DF_7 \rvert$	Fourier descriptors	Zahn and Roskies, 1971
γ	$FM_1 \ldots FM_4$	Flusser and Suk invariant moments	Sonka *et al.*, 1998
γ	$FZ_1 \ldots FZ_3$	Gupta and Srinath invariant moments	Sonka *et al.*, 1998
γ	(a_e, b_e)	Major and minor axis of fitted ellipse	Fitzgibbon *et al.*, 1999
γ	a_e/b_e	Ratio of major to minor axis of fitted ellipse	Fitzgibbon *et al.*, 1999
γ	$\alpha\ (i_0, j_0)$	Orientation and center of the fitted ellipse	Fitzgibbon *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	$K_1 \ldots K_3$	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[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[a]	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	$\bar{Q}$	Mean of BCLP[a]	Mery, 2003
I, R, G, B	$F_1 \ldots F_{15}$	First components of DFT of BCLP[a]	Mery, 2003
I, R, G, B	$\phi'_1 \ldots \phi'_7$	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[b] 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[a]	Castleman, 1996
L	L*a*b*	Color components of the region	Hunt, 1991; Papadakis *et al.*, 2000

Reprinted from Pedreschi *et al.*, ©2004, by courtesy of the Institute of Food Technologists.
γ, geometric features; I, intensity features; R, red component features; G, green component features; B, blue component features, L, L*a*b* features.
[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: 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, two measures of correlation information, and maximum correlation coefficient, for a distance of *d* pixels.
[c]The transformation takes a re-sized window of 32 × 32 pixels which includes the middle of the potato chips.

3 Applications

3.1 Sorting of potato chips

Recently, the different features of color, size, shape, and texture have been combined for their applications in the food industry, because in this way they increase the performance of the methods proposed. These features can be applied with various kinds of food,



L*: 58.743568
a*: 8.0011638
b*: 26.339806

L*: 38.099905
a*: 13.974827
b*: 19.029009

Figure 22.4 The color of a complete potato chip and a small circular browned region of it in L*a*b* units. (Reprinted from Pedreschi *et al.*, 2006©, courtesy of Elsevier.)

such as in fried potatoes for the detection and segmentation of surface defects, the prediction and characterization of chemical and physical properties, and the evaluation and determination of sensorial characteristics (Pedreschi *et al.*, 2004).

3.1.1 Color

The color of potato chips is an extremely important quality attribute and a fundamental criterion for the potato-processing industry, since it is strictly related to consumer perception, the Maillard reaction, and acrylamide formation (Scanlon *et al.*, 1994; Mottram and Wedzicha, 2002; Stadler *et al.*, 2002; Pedreschi *et al.*, 2006). These reasons make extremely important to have methods for measuring the color of potato chips properly (Pedreschi *et al.*, 2005; León *et al.*, 2006).

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 color of fried potatoes is usually measured usually in the unit of L*a*b*, using either a colorimeter or specific image-acquisition and processing systems. Parameter 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 two chromatic components, which range from –120 to 120 (Papadakis *et al.*, 2000). In the L*a*b* space the color perception is uniform, which means that the Euclidean distance between two colors corresponds approximately to the color differences perceived by the human eyes (Hunt, 1991). More recently, potato-chip color has been measured with computer vision techniques (Scanlon *et al.*, 1994; Segnini *et al.*, 1999; Marique *et al.*, 2003; Pedreschi *et al.*, 2004). Computer vision (CV) is used to measure the color of potato chips objectively, as it provides some obvious advantages over a conventional colorimeter – namely, the possibility of simultaneously analyzing the whole surface and the details of the chip, and quantifying characteristics such as brown spots and other appearance defects on the surface (Figure 22.4).

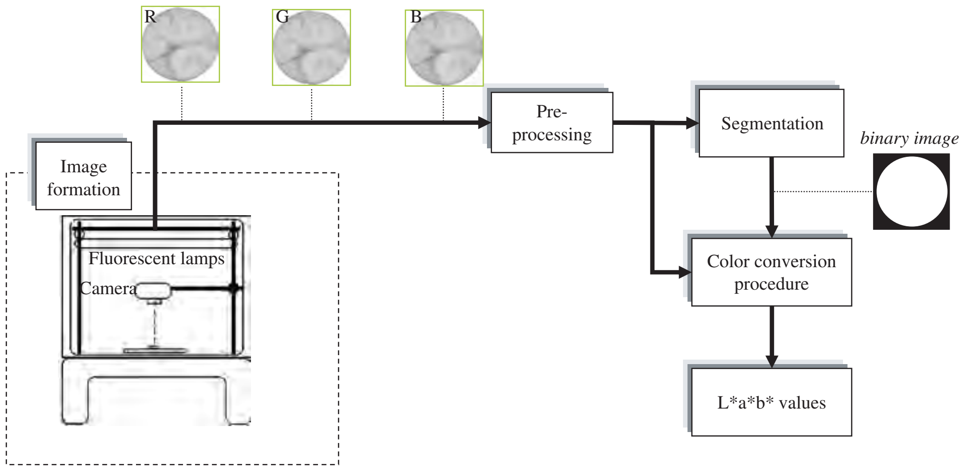


Figure 22.5 Schematic representation of a computer vision system used to covert color images from RGB to L*a*b* space. (Reprinted from Pedreschi *et al.*, 2006©, by courtesy of Elsevier.)

3.1.1.1 *Color models*

The use of CV for the color assessment of potato chips requires an absolute color calibration technique based on a common interchange format of color data and the knowledge of which features can be best correlated to the 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, which depend on the color model being used (Forsyth and Ponce, 2003). The most frequently used color model is the RGB model, in which each sensor captures the intensity of the light in the red (R), green (G) and blue (B) spectra respectively. There have been two trends recently in the application of image color for food quality evaluation: one is to carry out a point analysis, encompassing a small group of pixels for the purpose of detecting small characteristics of the object; the other is to carry out a global analysis of the object under the study of the color histogram in order to analyze its homogeneity (Brosnan and Sun, 2004; Du and Sun, 2004).

Pedreschi *et al*. (2006) recently designed and implemented a CV system to measure representatively and precisely the color of highly heterogeneous food materials, such as potato chips, in L*a*b* units from RGB images (Figure 22.5). Since 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 from the RGB images by testing five models: linear, quadratic, gamma, direct, and neural network. After the evaluation of the performance of the models, the neural network model was found to perform the best, with an error of only 0.96 percent. The network architecture is shown in Figure 22.6.

Finally, in order to show the capability of the proposed method, León *et al*. (2006) compared the color of a potato chip measured by this approach with that obtained by a Hunter Lab colorimeter. The colorimeter measurement was obtained by averaging 12 measurements (at 12 different places on the surface of the chip), whereas the measurement using the digital color image was estimated by averaging all pixels of the surface image. Measurement from the colorimeter was used as the standard measurement.

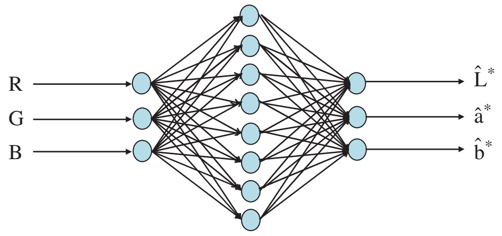
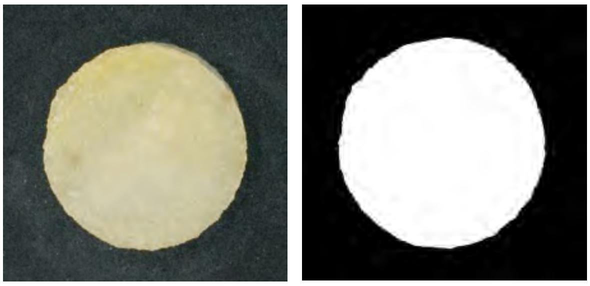


Figure 22.6 Architecture of the neural network used to estimate L*a*b* values from RGB images. (Reprinted from León *et al.*, 2006©, by courtesy of Elsevier.)



(a) (b)

Instrument	L^*	a^*	b^*
Hunter lab	61.7	−1.7	26.6
Digital image	66.9	−1.3	27.3

(c)

Figure 22.7 Estimatation of L*a*b* values of a potato chip: (a) RGB image; (b) segmented image by the method proposed by Mery and Pedreschi (2005); (c) color measured in L*a*b* space using a commercial colorimeter and the approach of León *et al.* (2006). (Reprinted from León *et al.*, 2006©, by courtesy of Elsevier.)

The results are summarized in Figure 22.7, and the error of the CV system was only 1.8 percent.

3.1.1.2 *Classification techniques*

A pattern-recognition approach was used for the classification of potato chips processed under six different conditions, and good classification results were obtained (Pedreschi *et al.*, 2004). Pedreschi *et al.* (2004) implemented an approach to classifying potato chips using pattern recognition from color images where more than 1500 features were extracted from each of the 60 potato images tested. The feature selection was carried out based on the Sequential Forward Selection (SFS) method (Jain *et al.*, 2000). Finally, 11 features were selected according to their classification attributes. Although samples were highly heterogeneous, classification of the potato chips using a simple classifier and just a few features was able to obtain a very good performance (accuracy $\geq$ 90 percent) in all cases. These authors showed that pattern-recognition techniques could easily and successfully be applied to classify highly heterogeneous materials such as fried potato chips processed under different conditions, as well as other food products.

Marique *et al.* (2003) used an artificial neuronal network to classify fried potato chips. In this approach, gray-level features of the apex, the center and the base of each potato chip were obtained from a color image in order to determine the quality class

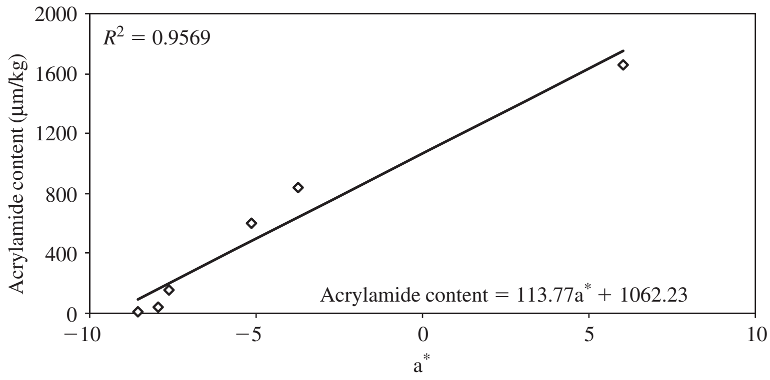


Figure 22.8 Acrylamide content vs color parameter a* of controlled and blanched potato chips (moisture content of ~1.8%, wet basis) fried at 120, 150, and 180°C. (Reprinted from Pedreschi *et al.*, 2005©, by courtesy of Elsevier.)

to which each chip belonged. Using a relatively small number of samples, the authors obtained good agreement with human inspectors, yielding a classification performance of around 90 percent.

3.1.1.3 *Color and frying temperature*

Color has been extensively used for evaluation of the effect of different temperatures on the quality of fried potato chips. The kinetics of color changes in potato slices during frying at four temperatures were investigated using the CV system implemented by Pedreschi *et al*. (2006). Furthermore, Pedreschi *et al*. (2005) found a good linear correlation ($r^2 = 0.9569$) between the acrylamide content of potato chips (moisture content ~1.8 percent on a wet basis) and their color represented by the redness component a* in the range of the temperatures studied. The redness component a* is an indicator of non-enzymatic browning; the lower a* value, the paler the potato chip (Figure 22.8). As the frying temperature increased from 120° to 180° C, the resultant chips became redder and darker as a result of non-enzymatic browning reactions that are highly dependent on oil temperature. Blanching reduced the a* value of potato chips due to the leaching out of reducing sugars previous to frying, thus inhibiting non-enzymatic browning reactions and leading to lighter and less-red chips. Figure 22.9 shows how the potato chips increased in redness and became darker as the frying temperature increased from 120° to 180° C. At the same frying temperature, blanching pre-treatment led to paler potato chips after frying.

3.1.2 Texture

Computer analysis of the surface texture of foods is of interest, because it affects the processing of many food products. 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

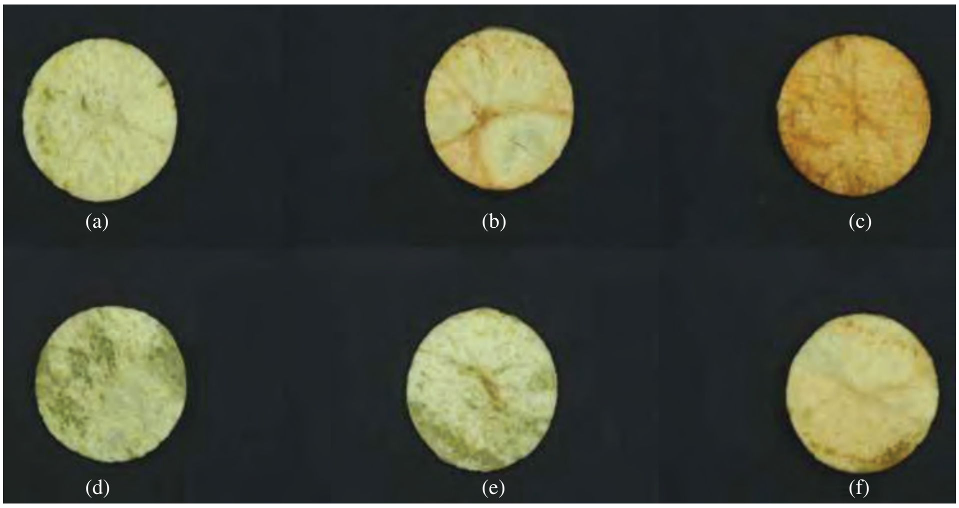


Figure 22.9 Images of potato chips (moisture content of ~1.8%, wet basis): (a) control fried at 120°C; (b) control fried at 150°C; (c) control fried at 180°C; (d) blanched fried at 120°C; (e) blanched fried at 150°C; and (f) blanched fried at 180°C. Controls are unblanched slices. Blanching treatment was in hot water at 85°C for 3.5 min. (Reprinted from Pedreschi *et al*., 2005©, by courtesy of Elsevier.)

quantify the important changes in the surface texture of potatoes during frying, such as the area-scale fractal complexity (Asfc) and the smooth-rough crossover (SRC). Another way to perform fractal analysis or to quantify the textural properties of a surface is by using the information contained in images (brightness as a function of position), with the advantage that the topography of the sample is not necessarily correlated with the texture of its surface image (Rubnov and Saguy, 1997; Quevedo *et al*., 2002).

Texture has been used in the quality inspection of potato chips. First, textural features are acquired from images taken of the surfaces of a set of potato chip samples by using video cameras. An identical set of samples of potato chips is used to obtain the quality attributes of the samples, using sensory panellists 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, the qualities of different categories of potato chips can be predicted by using their texture features from the images (Pedreschi *et al*., 2004).

Different problems involving appearance are associated with frying potato pieces (either slices or strips). One is the presence of defects such as black dots and necrosis. Searching for such defects involves on-line screening and eventual rejection of every defective chip (Marique *et al*., 2003). Another is the development of dark coloration because of the Maillard reaction between reducing sugars and amino groups (Márquez and Añón, 1986). This must be assessed at the laboratory for every sample in the potato batch intended for processing, because tubers that look perfectly healthy can develop intensive and heterogeneous browning or dark tips, which lead to consumer rejection. Defective batches are refused, to the disadvantage of the producer.

3.2 Browning evaluation

Evaluation of browning of samples taken from the frying lines must also be performed frequently at the laboratory, to police the process. The synthesis of acrylamide during frying increases brownness, due to the reaction of asparagine and reducing sugars (Pedreschi *et al*., 2005). As this reaction pathway is clearly correlated with the Maillard reaction (Mottram and Wedzicha, 2002; Stadler *et al*., 2002; Pedreschi *et al*., 2005), it has been proposed by several authors that quick and easy measurement of browning can be performed using image analysis rather than painstaking chromatographic methods (Pedreschi *et al*., 2005). Acrylamide is suspected to be a molecule with significant toxicological effects – carcinogenic, neurotoxic, and mutagenic (Rosen and Hellenäs, 2002).

3.2.1 Using artificial neural networks (ANN) by CARAH (Centre pour l'Agronomie et l'Agro-industrie de la Province de Hainaut, Belgium)

To estimate the darkening of French fries during frying, a simple frying assay is performed for 3 minutes at 180°C on 20 French fries obtained from the central part of 20 different potatoes. Each of the French fries is then assigned a category by visual examination under standard white light (Marique *et al*., 2003). The assessors build their evaluation with the help of a standard reference card (Figure 22.10), determined from both the overall darkening of individual French fries, and the contrast between the extremities (apex and base) and the center of the fries. Heterogeneous dark coloration is also penalized.

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

Artificial neural networks (ANNs) can attain very good performance when used to predict values for complex non-linear systems (Mittal and Zhang, 2000; Wilkinson and

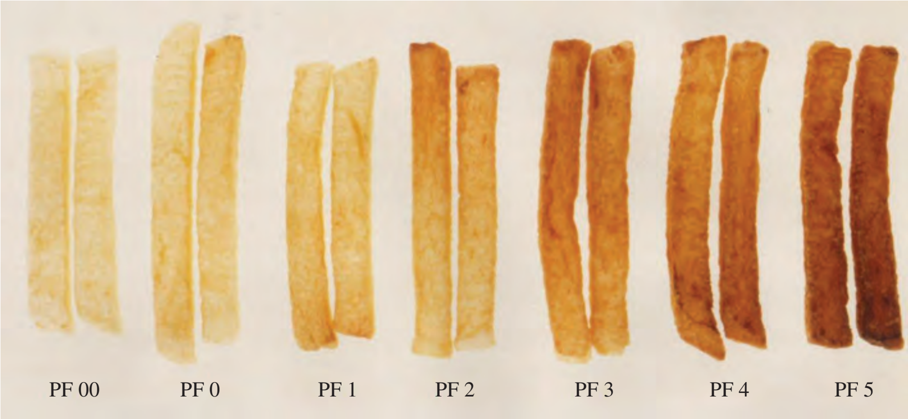


Figure 22.10 A reading card of French fries for browning categories.

Yuksel, 1997). Moreover, they are endowed with a broad capacity for generalization, so that they can give useful information for cases that are not part of their training set (Schalkoff, 1997; Wilkinson and Yuksel, 1997; Marique and Wérenne, 2001; Yang *et al*., 2002). They appear to be the logical choice for achieving successful prediction of the darkening index for fried potatoes.

Marique and colleagues (2003) used image analysis to extract gray-level intensities from an image data bank gathered from the 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 individual French fries, corresponding to the mean gray values at the apex, center, and base of the specimen, respectively. The ANN is a feed-forward network consisting of three inputs, a hidden layer of four neurons with sigmoid transfer functions and bias (Figure 22.11), and an output layer presenting a single linear neuron with bias that is issued to 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 each of the French fries to a color category ranging from 0 (very pale) to 4 (very dark). The Lenvenberg–Marquardt algorithm gave fast convergence, as is usually the case for small networks. Figure 22.12 shows how the assessor assigns a particular color value to individual French fries. The different color categories are distributed throughout the gray-value scale, and there is partial overlapping. This comes from the fact that when a particular specimen stands exactly

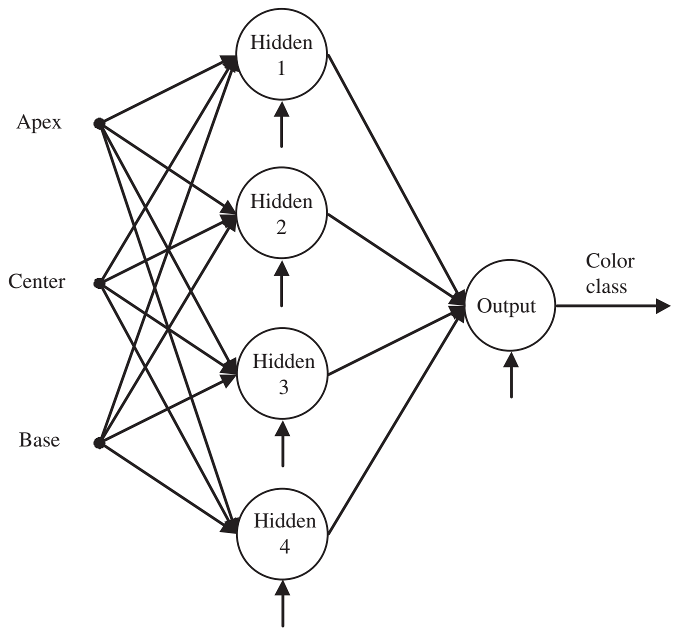


Figure 22.11 Structure of a two-layer feed-forward artificial neural network with three inputs, four hidden neurons with bias, and one output neuron with bias. (Reprinted from Marique *et al*., 2003©, courtesy of Institute of Food Technologists).

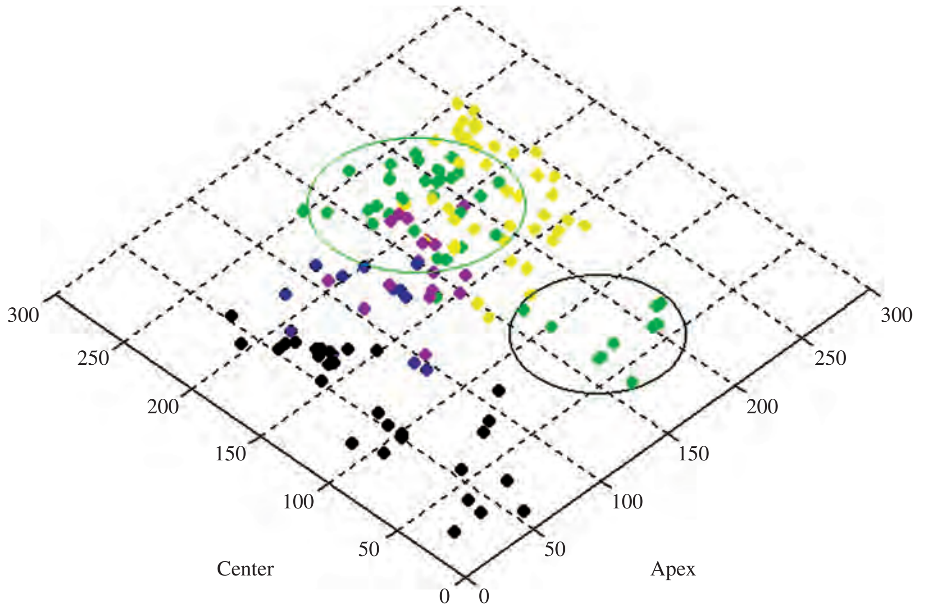


Figure 22.12 Mean gray values of the center and apex of French fries. The color code indicates the class of color: very pale gray, 0; pale gray, 1; mid-gray, 2; dark gray, 3; black, 4. The ellipsoids contain the two sub-populations of class 1: dark gray, globally darker fries; pale gray, paler fries with contrasted dark ends. (Reprinted from Marique *et al*., 2003©, courtesy of Institute of Food Technologists).

between two categories, the assessor will select one at random and either undervalue or overvalue it, which hence leads to the overlapping.

French fries are assigned to category 0 if they appear both very pale (gray levels over 150) or rather paler at the extremities than in the center. A specimen will be assigned to category 1 for one of the following two reasons: it appears paler in the center but has contrasting dark ends (global appearance), or it appears dark in the center with paler ends. Category 1 is thus clearly split in two subpopulations (see ellipsoids in Figure 22.12) flanking both sides of category 0. Categories 2, 3, and 4 then progressively regroup darker French fries, which are generally pale in the center with more or less contrasted dark ends. Thus, it is only for the two lower color categories that the assessor will overvalue a specimen possessing dark contrasted extremities. For higher color categories, estimations are based mostly on the global (center) appearance of French fries, where dark contrasted ends are considered to be "normal" (Marique *et al*., 2003).

The trained ANN was used to generate a complete set of predictions for the different possible combinations of gray levels of the center and the apex of the French fries. This is illustrated in Figure 22.13, where computation was performed using equal gray values for both the base and the apex of the fries. The ANN showed a good performance, with correlation coefficients of 0.972 for the training data and 0.899 for the validation data. The network displays complex and continuous behavior for the low color categories 0, 1, and 2, but operates a discrete classification between categories 3 and 4. This could be a

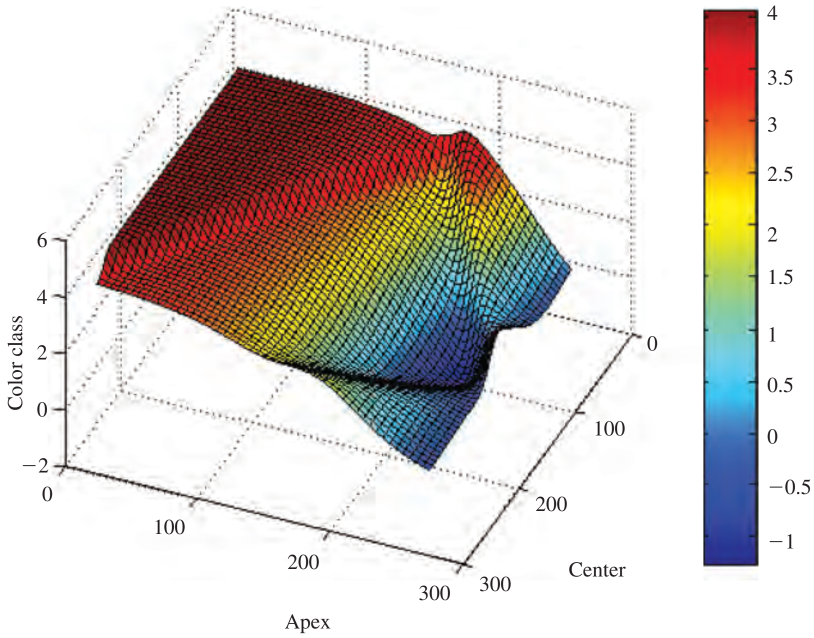


Figure 22.13 Response of the artificial neural network: color class categories are described as a function of all possible combinations of gray levels of the center and the apex of French fries. (Reprinted from Marique *et al*., 2003©, by courtesy of Institute of Food Technologists).

consequence of both the greatest number of data points for high color categories, and the more complex behavior of the assessor for low color categories (Marique *et al*., 2003).

A more complete simulation is shown in Figure 22.14, illustrating the discrete color categories (the values predicted from the ANN are approximated by the nearest integer) obtained for all the possible combinations of gray levels of the three regions of the fries. Again, more complex behavior is observed for the lower color categories. The intermediate categories 2, 3, and 4 also extend between two "wings," being either globally paler with dark ends or globally darker with pale ends. Color classification varies most with the apex and center gray values (Marique *et al*., 2003).

3.2.2 Using other methods (Walloon Agricultural Research Center, Belgium)

This research center, affiliated to the Gembloux Agricultural University in Belgium, has developed a home-made system for the quality evaluation of French fries (Figure 22.15). In the system, 20 French fries are cooked and arranged on a tray with a reference tongue (Figure 22.16). The reference tongue is directly extracted from the USDA reference card in order to represent the seven reference colors on each sample. For each image, a tray contains 20 French fries and a reference tongue. The tray is then placed in the box and an image is taken.

Image analysis is performed using Image Pro Plus software 6 (Media Cybernetics, USA). The program checks the number of references, which are represented by the seven colored squares arranged on each tray, and offers a manual correction in cases

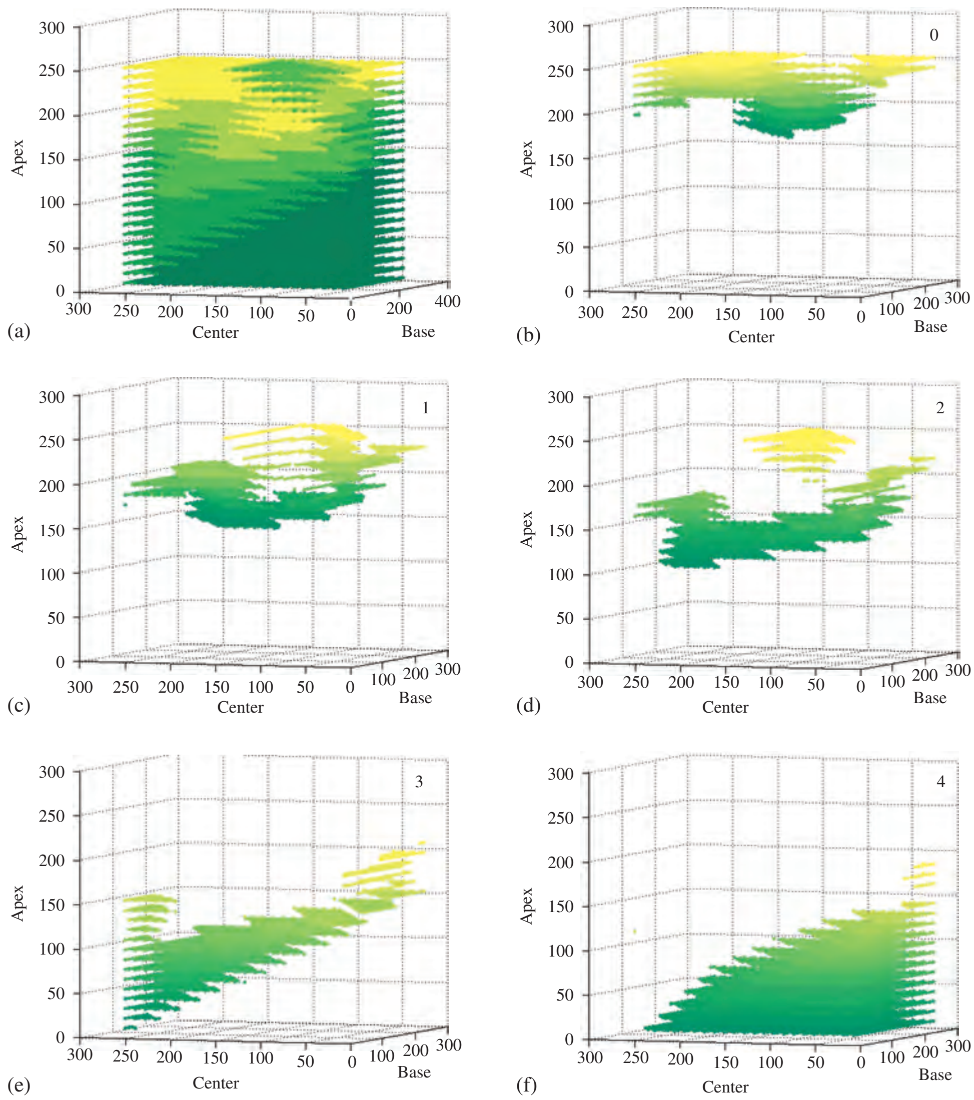


Figure 22.14 Discrete color categories obtained from all the possible combinations of gray levels for the three regions of the French fries: (a) general presentation; (b)–(f) partial views of each color category, from 0 (b) to 4 (f). (Reprinted from Marique *et al.*, 2003©, by courtesy of Institute of Food Technologists).

where this number is different from seven. The references are then scanned. The French fries are also scanned and counted. Once this has been done, macro sequences successively comply in a few seconds (via sending data to Excel) to compare the colors of the French fries with the reference tongue in order to determine the color parameters. For this comparison, RGB images are first converted into gray-scale and their luminous intensity is then estimated. These stages are repeated until there is automatic generation of a detailed written (containing photographs of the sample, the date, color parameters etc.) and archived report.

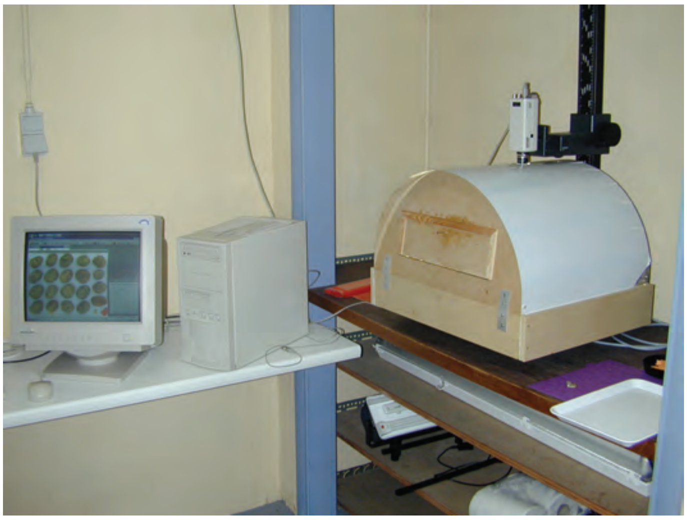


Figure 22.15 Device for quality evaluation of French fries (Gembloux Agricultural University in Belgium).

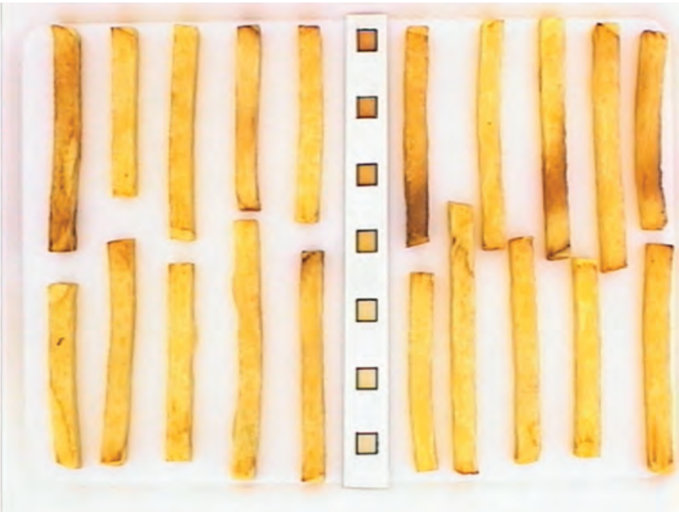


Figure 22.16 Tray ready for image analysis with 20 French fries and 7 colored squares.

In order to compare the image analysis method with sensory analysis (visual comparison), a series of 100 samples is first analyzed using both methods. The correlation of the results between the two methods is 0.951, which is a very good result compared with the weak repeatability of the reference method (Figure 22.17).

3.2.3 Browning-sorting and acrylamide estimation using ANN by CARAH

Determination of the acrylamide concentration nowadays appears to be necessary since very high concentrations of this potentially toxic molecule are detected in amylaceous

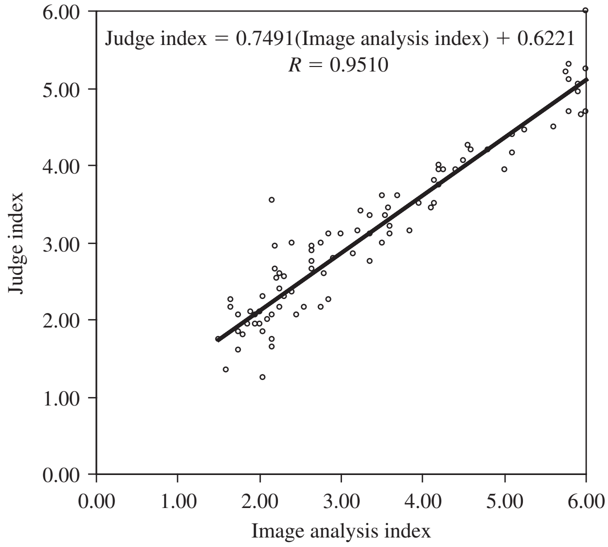


Figure 22.17 Correlation between the visual measurements and those by image analysis.

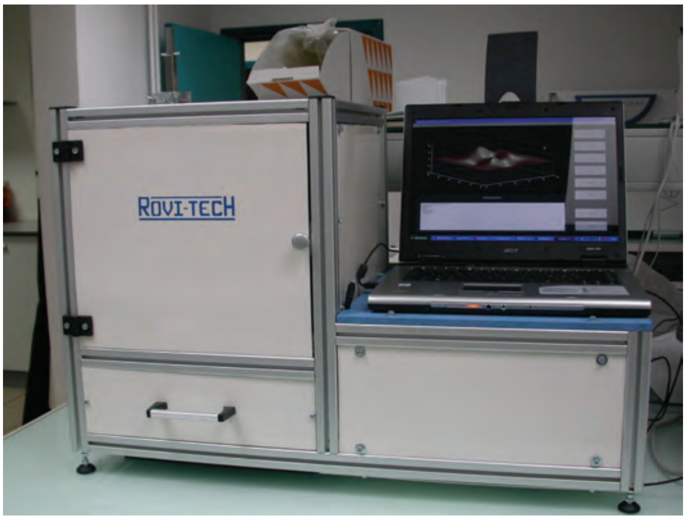


Figure 22.18 Artificial neural network imaging system for the determination of color class and acrylamide concentration in French fries.

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 techniques based on image analysis of the browning of French fries to measure the acrylamide concentration. It was known that there would be good correlation between non-enzymatic browning development and acrylamide formation, since several studies had reported a strong linear relationship between browning and acrylamide accumulation in fries (Mottram and Wedzicha, 2002; Stadler *et al*., 2002; Pedreschi *et al*., 2005).

CARAH and a Belgian industrial partner, Rovi-Tech s.a. (Presles, Belgium), have developed a high-speed imaging system incorporated with ANN. Snapshots of every one of the French fries tested are taken and then results for both color category and acrylamide concentration are obtained (Figure 22.18). The system is intended to analyze incoming potato batches of pre-fried French fries for quality control in food distribution. The heart of the system is Rovi-Tech's ILB-25 (Image Learning Box), a very efficient ANN that allows easy and powerful correlations of complex visual data analysis.

4 Conclusions

Both gray-scale and color images of potato chips are useful for extracting image features for an appropriate classification. The most relevant features for potato-chip classification are either texture or color from L*a*b* space. Potato chips can be properly classified to obtain very good values, despite their high heterogeneity. The automatic classification methodology proposed for potato chips has a wide range of potential uses.

The computer vision system described in this chapter allows determination of the color of potato slices in L*a*b* color space that is transformed from the RGB space in an easy, precise, and objective way. To achieve this, image pre-processing and segmentation is performed. The computer vision system allows easy measurement of color not only over the entire potato chip surface, but also at small, specific regions of interest.

Five models that can measure the color in potato chips using the color of each pixel on the target surface, which cannot be accessed with conventional colorimeters, have been built. The best results were achieved by the quadratic and neural network models, both with small errors of close to 1 percent.

For both control and blanched potato chips, acrylamide formation decreases dramatically as the frying temperature decreases from 180° to 120°C. There is a linear correlation between non-enzymatic potato-chip browning quantified by computer vision and the corresponding acrylamide values.

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