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Computer vision techniques for modelling the roasting process of coffee (*Coffea arabica* L.) var. Castillo

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Abstract: Artificial vision has wide-ranging applications in the food sector; it is easy to use, relatively low cost and allows to conduct rapid non-destructive analyses. The aim of this study was to use artificial vision techniques to control and model the coffee roasting process. Samples of Castillo variety coffee were used to construct the roasting curve, with captured images at different times. Physico-chemical determinations, such as colour, titratable acidity, pH, humidity and chlorogenic acids, and caffeine content, were investigated on the coffee beans. Data were processed by (i) Principal component analysis (PCA) to observe the aggrupation depending on the roasting time, and (ii) partial least squares (PLS) regression to correlate the values of the analytical determinations with the image information. The results allowed to construct robust regression models, where the colour coordinates (L^*, a^*), pH and titratable acidity presented excellent values in prediction (R^2_{Pred} 0.95, 0.91, 0.94 and 0.92). The proposed algorithms were capable to correlate the chemical composition of the beans at each roasting time with changes in the images, showing promising results in the modelling of the coffee roasting process.

Keywords: Colombian coffee; visible spectrum; image processing; chemical composition

Colombian coffee is recognised worldwide and has been an international price leader since, at least 1997 (Barjolle et al. 2017). In particular, the Huila region produces the largest quantity of specialty coffees in the country, and despite the high volumes of production, artisan processing techniques are still used. It is therefore important to find low cost techniques for optimising, modelling, and controlling coffee processing and, thus, improving production efficiency. In the transformation chain, the roasting process is important given its effect on the final product. The coffee-roasting is divided into three phases: drying, features development and cooling (Fadai et al. 2017), in which changes in the colour and shape are presented. Currently, there is an increasing demand for real-time approaches such as computer vision technology to monitor and control the food quality indicators including shape, size, colour, and texture during drying process (Aghbashlo et al. 2014). The visual evaluation of food quality involves the recognition of visual patterns, where the objective is to detect specific patterns in foods related to relevant quality standards. In addition, a wide variety of algorithms have been published in the literature with several applications in food for quality assessment (Mery et al. 2013). In this respect, a number of studies have been conducted to optimise the coffee roasting step using image analysis, and many of these works are based on the infrared spectrum (Alessandrini et al. 2008; De Luca et al. 2016; Santos et al. 2016a; Santos et al. 2016b), which involves the use of expensive equipment. Other studies use inexpensive and easy to apply tools to monitor coffee roasting (Hernández et al. 2008; Gabriel-Guzmán et al. 2017; Sarria-González et al. 2019) but do

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not relate the results with the compositional properties of the beans.

Most coffee roasting machines are designed to reach a temperature that remains constant in which coffee beans are heated at high temperatures (160–240 °C) for times ranging between 8 and 20 min depending on the desired characteristics of the final product (Fabbri et al. 2011). Expert roasters use a set of auditory and sensory indicators and personal experience (Wieland et al. 2012) to determine an appropriate time to obtain the perfect roasting degree, in which desirable characteristics are developed. To avoid roasted beans that do not develop the adequate features to deteriorate the quality of the batch, a measurement system can be used to help determine the appropriate roasting degree.

The aim of this study was to evaluate the coffee roasting step using computer vision techniques in the visible spectrum and its correlation with the coffee beans' physico-chemical parameters.

MATERIAL AND METHODS

Arabica coffee (*Coffea arabica* L.) var. Castillo (30 kg) was used for the experiments. Cherries with an intense red colouration were harvested in a farm located in Huila-Colombia (1°21'36.72" N, 77°17'03.01" W) at an altitude of 1 650 m above the sea level. The cherries were later transported to the Surcolombian University (Neiva, Colombia), then fermented for 18 h in plastic containers (19 × 23 × 30 cm) in which the beans reached a height of 10 cm. After fermentation, the beans processed by wet method were washed three times to remove the mucilage and, then, sun-dried (ambient temperature 27.9 ± 5 °C, RH (relative humidity) 64.6 ± 5 % and average wind speed 0.2 m s^{-1}) to obtain the parchment coffee. The final humidity content in the beans after sun-drying was between 10–12 %. Hulling was carried out in a laboratory hulling machine (ING-C-200; Ingesec, Colombia), followed by the selection of non-defective coffee beans in accordance with the provisions of the Specialty Coffee Association (SCA, 2018). The coffee beans were passed through a number 13.5 mm diameter sieve to eliminate smaller beans.

Coffee roasting and image acquisition

Green coffee (150 g) was processed in a TC 150R rotary drum roaster (Quantik, Colombia) at 180 ± 2.5 °C. The roasting time was defined until the beans were dark roast. To construct the roasting curve eleven sampling points, with interval times of 60 sec, were considered, in order to include the different roasting steps: green beans, light roast, medium roast, dark roast and burnt coffee. The roasting degree was determined by the L^* value (lightness) of the CIE (Commission Internationale d'Eclairage) L^*, a^*, b^* measurements, as follow: $24.50 < L^* < 26.00$ for light roast, $21.50 < L^* < 24.50$ for medium roast coffee, and $L^* < 21.50$ for dark roast coffee according to the literature (Wei et al. 2012); 24 samples were evaluated for each sampling time. Figure 1 shows the image acquisition and processing procedure, where

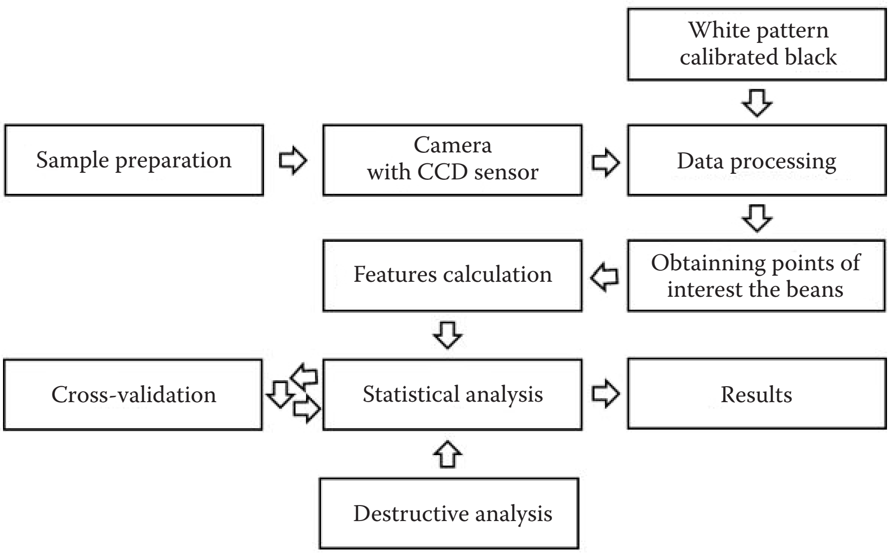

Figure 1. Schematic diagram of the procedure employed to predict roasting time

CCD – a charge-coupled device

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a charge-coupled device (CCD) T3 sensor (Canon, Japan) with 12 megapixels of resolution was adapted to a metal stand with a lighting arrangement using two LED bulbs dichroic 7.5 W, 620 Lm (Philips, Netherlands) that projected light onto the coffee samples, placed 40 cm from the objective in petri dishes. The lighting was left on until it reached a stable colour temperature of 5 500 °K prior to image acquisition.

The working conditions for the camera were: an aperture range of f/1.8 for the lens, with a focal length of 25 mm and a depth of field of 1.5 cm; the shutter time was adjusted according to the lighting, the camera›s best performance in the experiment conditions was obtained with a value of between 1/80 to 1/100 sec. Images were taken remotely to avoid manipulation of the camera and thus to maintain the accuracy of the system with a free version of Capture One PRO 10 software (Phase One, Denmark).

Image processing

A colour calibration was performed to normalise the non-linear light source reflectance. This was conducted by applying Equation 1:

$$R(x,y,c) = \frac{R_s(x,y,c) - R_d(x,y,c)}{R_w(x,y,c) - R_d(x,y,c)} \quad (1)$$

where: $R_W(x,y,c)$ – the reflectance value of a white pattern colour acquired under the same conditions (in pixels coordinates x, y and channel c), $R_d(x,y,c)$ – the dark measure covering the camera objective, $R_s(x,y,c)$ – the sample colour intensity.

An algorithm was developed to perform the image segmentation for each roasting time by calculating a mask for each capture. Consequently, a binarisation process was used to estimate the mask. To do so, images were converted from red (R), green (G) and blue (B) coordinates Figure 2A to a grey-level scale Figure 2B, to minimise the intraclass variance of the black and with pixels. The Otsu method (Otsu 1979) was applied to obtain a dynamic threshold to separate the coffee beans from the background (Vala & Astha 2013). Finally, morphologic operators were used to close the edge of the image and fill the hole by white pixels Figure 2C. Using the mask, the objects were correctly differentiated from the background image (Piccardi 2004).

Once the mask was superimposed on the RGB image, the background was eliminated Figure 2D. Then, the Watershed algorithm (Beucher & Meyer 1992) was used to calculate the edge of every single coffee bean Figure 2E where centroids were obtained; these centroids were used as points of interest to calculate features. For each centroid, a vector of 20 colour and morphological features were calculated. This vector was composed of the following colour features: RGB components and HSV (hue, saturation and value) components. The morphological components are the 14 texture values of Haralick et al. (1973). To correct outlier values and redundant information, a dynamic colour filter was designed to remove the points of interest that do not contain useful information. In this regard, an RGB histogram of 64 levels was calculated to remove the points of interest with zero intensity (holes between beans) and belonging to the fourth quartile (removing specular highlights and outliers). Then, for each image, a vector of 44 features was generated using the filtered centroids. This vector was composed of the statistical parameters (mean, median, standard deviation, maximum and minimum value) from the colour coordinates (30) and the mean value of Haralick (1973). The images were processed using MATLAB 8.0 software (Mathworks, USA).

Destructive analyses, analytical determinations

Colour measurements. An volume of 40 cm^3 of each sample was taken shortly after roasting the beans to perform the colour measurements using a CR-410 Colourimeter (Minolta Chroma Meter; Japan). The colour system employed was CIE L^*, a^*, b^* and a D-65 illuminant, the instrument was previously calibrated with a white standard (87.316.3231).

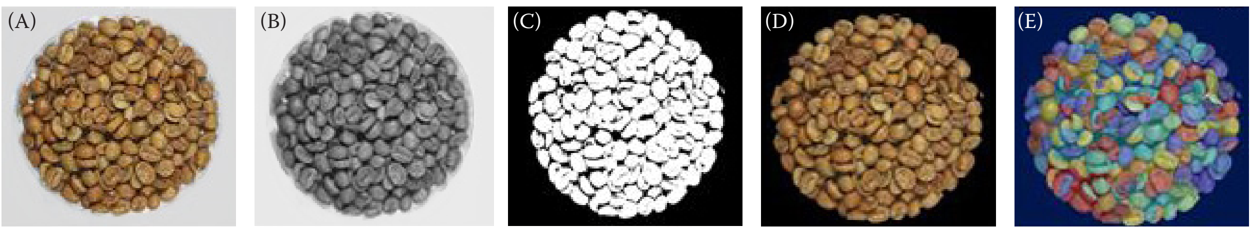

Figure 2. RGB (red-green-blue model) image (6 min of roasting) (A); grey-level scale image (B); binary mask from the same image (C); segmented image (D); application of watershed algorithm (E)

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Determination of pH and titratable acidity. Titratable acidity was evaluated by titration with NaOH, according to the procedure described by Rodríguez et al. (2020). The results were expressed in milligrams (mg) of chlorogenic acids (CGAs) in relation to grams (g) of coffee. The pH determinations were performed following the method described by (Mazzafera 1999).

High performance liquid chromatography analysis. Caffeine and CGAs were measured using a Hitachi LaChrom Elite liquid chromatograph (Hitachi Ltd., Japan) equipped with an auto-sampler (model L-2200) and UV detector (model L-2400). Ground coffee and MgO (0.5 g each) were combined in 25 mL of deionised water and stirred for 20 min at 90 °C in a water bath. The solution was cool down, and paper filtered (Whatman No. 1; Sigma-Aldrich, UK); then, coffee extract was diluted with deionised water (2 : 10 volume ratio) and filtered through a 0.20 μm syringe filter. Separation was carried out with a Kromaphase 100 C18 analytical column (150 × 4.6 mm i.d., 5 μm) (Scharlab, Spain). The mobile phase was prepared by mixing MeOH and water containing 0.1% phosphoric acid. UV detection was performed at 280 nm for caffeine and 324 nm for CGAs. In all cases, 10 mL was injected with a flow rate 1.2 mL min^{-1}.

Statistical analysis

Differences in physico-chemical parameters between samples of each roasting time were checked by an analysis of variance (ANOVA), considering each attribute as a dependent variable, and time as the factor. The level of significance setting was $P < 0.05$. To assess the feasibility of the image analysis technique and discriminate between different colour and volume levels, principal component analyses (PCAs) were carried out with the data obtained. partial least squares (PLS) were also carried out to create predictive models of coffee characterisation from the image measurements. Specifically, the SIMPLS (simple PLS) algorithm (De Jong, 1993) was employed. PLS prediction models were created using 80% randomly selected experimental data for the calibration set (65%) and the cross-validation set (15%), venetian blind cross-validation with ten data splits was carried out. The rest of the data (20%), which were not employed for building the models, were employed as a test set.

The model was then validated with a new set of experimental data (validation set). All statistical analyses were performed using Statgraphics centurion XVI. (Manugistics Inc., USA) and PLS Toolbox 6.3 (Eigenvector Research Inc., USA), a toolbox extension within the MATLAB 8.0 computational environment (The Mathworks, USA).

RESULTS AND DISCUSSION

Destructive analysis. Figure 3 shows the colour change presented by the coffee beans at the different roasting times, and the temperature at which the beans came out of the roaster. The curve starts with the green beans and continues at intervals of one minute. Light roast coffee was obtained in 7.00 ± 0.05 min, medium roast coffee was obtained in 7.40 ± 0.12 min and dark roast coffee in 8.05 ± 0.09 min. As the tempera-

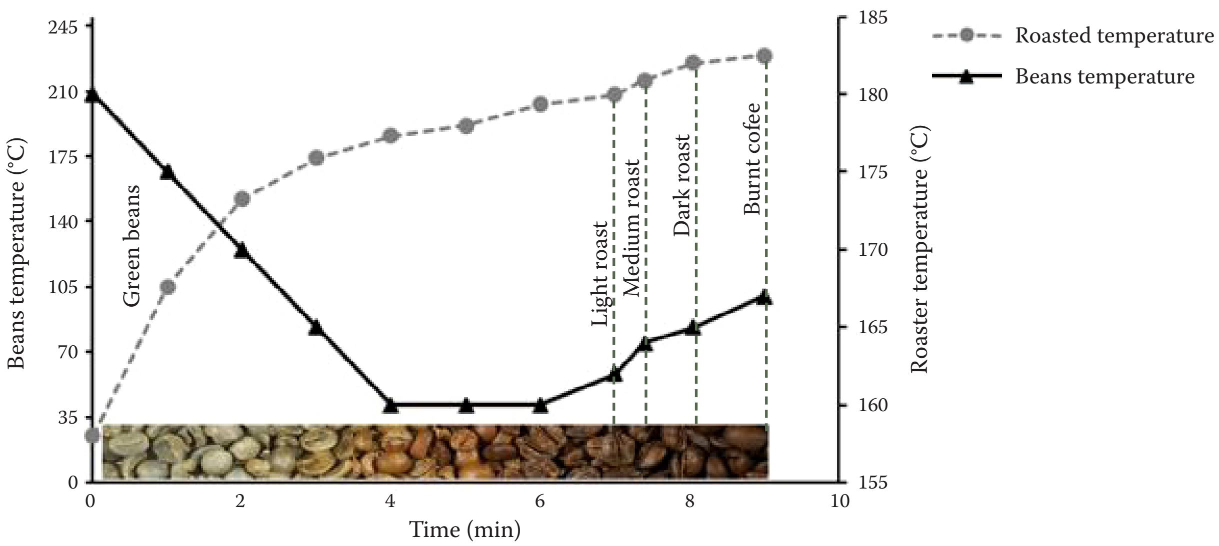

Figure 3. Changes in coffee roasting: bean temperature (y-axis on the left) and roaster temperature (y-axis on the right) in function of the processing time (x-axis)

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ture of the roaster increased, the beans presented noticeable browning and their volume increased gradually, once the coffee temperature reached approximately 170 °C, the caramelisation and Maillard reactions start, these reactions generate the colour, flavour and aromas of typical roasted beans (Wang & Ho 2013).

Figure 4 shows the colour coordinates of the beans for each roasting time, with significant differences ($P < 0.05$) for the three values. It was observed that the lightness (L^*) values decreased as the temperature increased, the green-red coordinate (a^*) shows the maximum values after five minutes of roasting, when the beans temperature was 191.6 ± 1.5 °C, then a slight decrease was observed, while the blue-yellow coordinate (b^*) exhibited the maximum values after four roasting minutes when the coffee beans had reach a temperature of 185.9 ± 1.9 °C, and subsequently the values decreased to below those obtained for green beans. The concentration of brown pigments is affected by the degree of roasting; usually green arabica beans contain free amino acids and saccharides, which can combine with each other and causes the Maillard reactions of condensation (Budryn et al. 2009), which is reflected in the colour changes from green-yellow to orange-brown. The values subsequently declined as the beans became darker, specifically for the L^* and b^* coordinates.

Table 1 shows the results of the analytical determinations of pH and titratable acidity. There were significant differences ($P < 0.05$) for both determinations. The pH values remained constant during the first three roasting minutes, and this was followed by a gradual increase until the beans reached a medium roasting degree (7.4 min) where the values were similar until reaching a dark roast. The formation of acids such as glycolic, lactic, formic, and acetic, are considered to a key factor in the pH obtained at medium roasting degree (Ginz et al. 2000). The titratable acidity increased along with the roasting time, the highest lev-

Table 1. Mean value and standard deviation (SD) of changes in pH and titratable acidity of Castillo variety samples throughout the roasting process ($n = 9$; $P < 0.001$)

Time (min)	pH	Titratable acidity (mg g^{-1})
0.0	6.07 ± 0.01^{a}	2.97 ± 0.18^{ab}
1.0	6.00 ± 0.05^{a}	3.22 ± 0.60^{ab}
2.0	6.05 ± 0.07^{a}	2.50 ± 0.60^{a}
3.0	6.06 ± 0.11^{a}	4.29 ± 1.57^{b}
4.0	5.84 ± 0.12^{b}	6.44 ± 1.69^{c}
5.0	5.67 ± 0.09^{c}	8.95 ± 1.26^{d}
6.0	5.30 ± 0.02^{d}	14.31 ± 1.01^{e}
7.0	4.95 ± 0.05^{e}	28.27 ± 2.45^{f}
7.4	4.87 ± 0.07^{ef}	37.22 ± 1.63^{g}
8.0	4.85 ± 0.00^{4f}	37.93 ± 1.20^{g}
9.0	4.93 ± 0.09^{ef}	37.57 ± 1.09^{g}

Different superscript letters show statistically significant differences

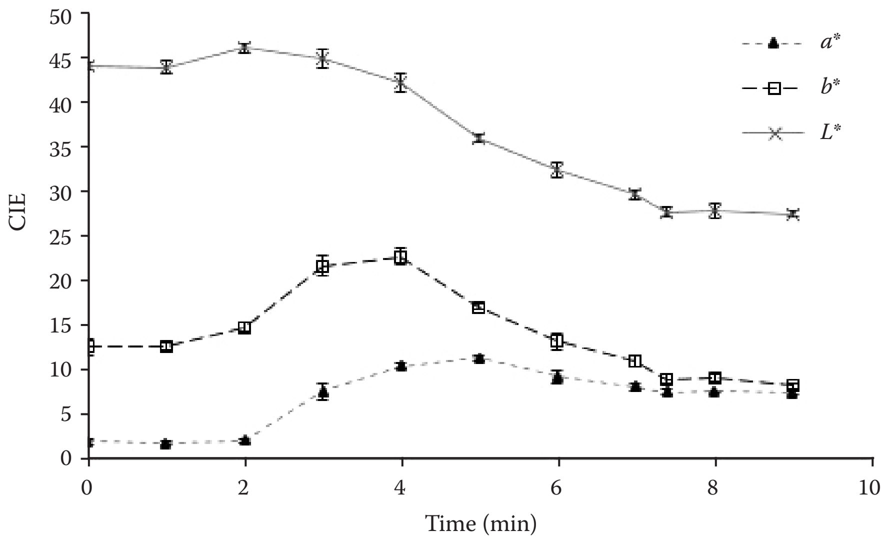

Figure 4. Mean values and standard deviation of colour coordinates (L^*, a^*, b^*) for Castillo variety samples throughout the roasting process

L^* – lightness; a^* – the green-red coordinate; b^* – the blue–yellow coordinate

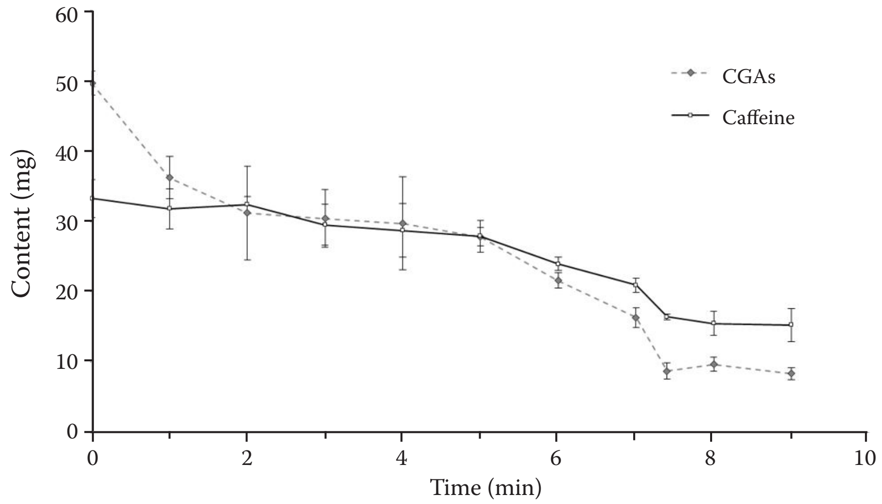

Figure 5. Mean values and standard deviation (SD) of chlorogenic acids (CGAs) and caffeine content of Castillo variety samples throughout the roasting process

els of acidity were observed in the interval time that goes from light to dark roast degree, a rapid increase of titratable acidity was observed as green coffee beans were light and medium roasted (Wang & Lim 2012).

Figure 5 shows the results for the content of CGAs and caffeine throughout the roasting process, significant differences ($P < 0.05$) were observed for the two parameters in relation to each roasting time. The CGAs were more sensitive to the temperature effect and presented losses up to 80.49 ± 1.99% (dark roast), while caffeine presented lower losses, 52.87 ± 8.58% for dark roast. Caffeine tends to be relatively stable to heat during roasting (Garg 2016), although it tends to present lower values in coffee that has been roasted at high temperatures than in coffee that has been roasted at low temperatures (Wang & Lim 2015).

Principal component analysis (PCA). Figure 6 shows the PCA performed with the information about the features obtained from the computer vision system. The first three components explain 90.94% of the variance of the model and it was observed that the data have a non-linear relationship. Samples formed three different clusters depending on the similarities in colour and volume features of the beans after the roasting time. The first group was obtained with the information of the green coffee beans and the roasting times

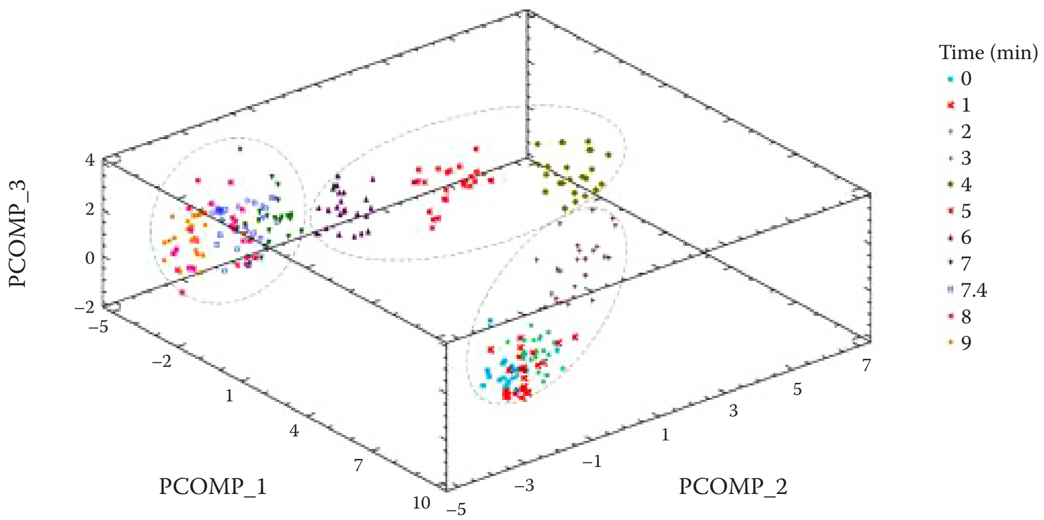

Figure 6. Principal components analysis (PCA) performed on image measurements of samples throughout the roasting step, explained variation 90.94%

PCOMP – Principal Component

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Table 2. Statistical results of the PLS models for the optimisation and control of the coffee roasting process.

	Time	L^*	a^*	b^*	pH	Titratable acidity	CGAs	Caffeine
RMSEC	0.69	1.57	0.91	1.44	0.11	4.04	5.82	3.48
RMSECV	0.70	1.67	0.95	1.51	0.11	4.14	5.81	3.77
RMSEP	0.71	1.68	0.95	1.54	0.12	4.10	5.83	3.89
R^2_{Cal}	0.94	0.96	0.92	0.89	0.95	0.92	0.82	0.77
R^2_{CV}	0.94	0.96	0.91	0.88	0.95	0.92	0.80	0.73
R^2_{Pred}	0.94	0.95	0.91	0.87	0.94	0.92	0.79	0.73

L^* – lightness; a^* – the green-red coordinate; b^* – the blue–yellow coordinate; CGAs – chlorogenic acids; RMSEC – Root Mean Square Error Calibration; RMSECV – Root Mean Square Error Cross-Validation; RMSEP – Root Mean Square Error Prediction; R^2_{Cal} – coefficient of determination of calibration; R^2_{CV} – coefficient of determination of cross-validation; R^2_{Pred} – predictive coefficient of determination

from minute one to minute three where the samples maintained a green colour. Another aggregation of data is presented at minutes four to six, related to the changes in colour presented in the beans, from green to light brown. This is because the temperature inside the beans reaches an average of 193.5 ± 8.71 °C. The third group is formed as the roasting continues, beans gradually darken until reaching minute seven when the temperature reaches 208 °C and samples exhibit a more homogeneous characteristic in colour and shape. When analysing the component loads, it was observed that the first component associates 56.81% of the variables, representing 40.91% of the colour and 50.00% of the shape variables, the second component associates 9.09% of both variables, and the third component represents the whole weight of the roasting time. When performing the variable selection, to improve the prediction performance, make the calibration reliable, and provide simpler interpretations (Yun et al. 2019), variables were reduced from 44 to 29, and when performing the PCA the explained variation was increased to 94.92%.

Partial least square (PLS). An PLS regression model was constructed to correlate the analytical determinations with the image variables. The adjustment selected was of two components that explained 94.22% for the data from the images and 89.56% of the variance for the information with the analytical determinations. This level was selected as a good value watching the variance trend of increasing the LVs (number of PLS factors-latent variables) to 8. Table 2 shows the statistical values of each of the PLS models estab-

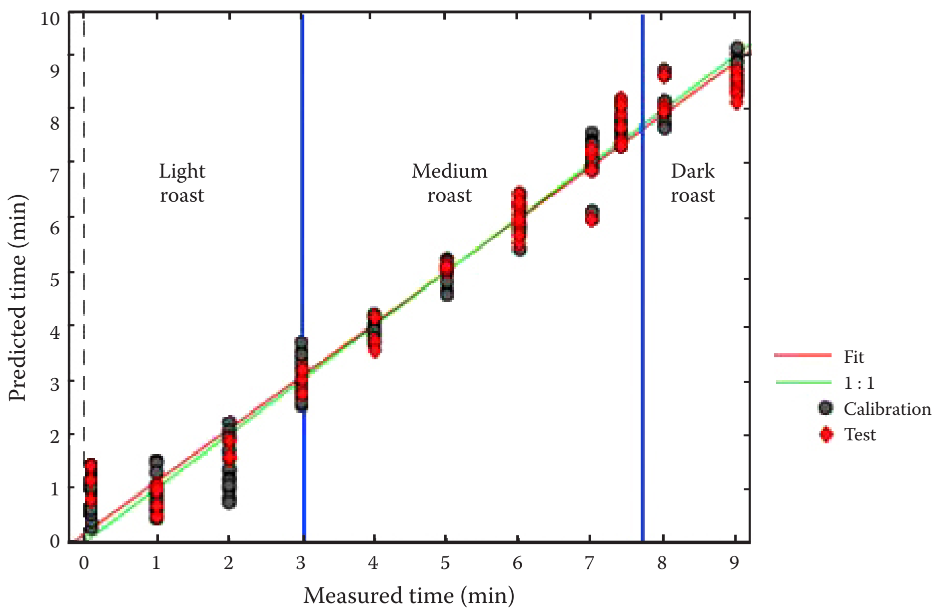

Figure 7. Partial least squares (PLS) regression for predicting the roasting time employing the image variable

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lished with the physico-chemical variables that were used to construct the predictive model. The results show a high degree of reliability for the regression of the roasting time (R^2_{Pred} = 0.94) because the colour and the texture change a lot during roasting. Although, as is shown in Figure 7. The three first minutes cannot be predicted due the low colour-texture changes (light roasting degree), later the regression line fits to the 1 : 1 line with a standard deviation of around 1 min (medium and dark roasting). In the same way, the image variables are understandably highly correlated with the colourimetry values (L^*, a^*, b^*) with a mean value of R^2_{Pred} 0.91. The pH, moisture content and the titratable acidity both present excellent regression values (R^2_{Pred} 0.94, 0.93 and 0.92) mainly because both change significantly throughout the roasting time. On the other hand, and for the same reason, CGAs and especially caffeine have lower values because their trending changes with the roasting time are lower. It should be noted that calibration, cross-validation, and prediction results are similar meaning that the models do not suffer from over fitting.

CONCLUSION

The developed computer vision system provides enough information about the roasting process with a reliable prediction of the relevant physico-chemical attributes in the coffee beans, including roasting time, colour coordinates, pH, titratable acidity, CGAs and caffeine content. The results obtained demonstrated that the developed technique can be applied to control and model the coffee roasting in a rapid and non-destructive systematic procedure.

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