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A computer vision system for coffee beans classification based on computational intelligence techniques

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ABSTRACT

Evaluating the color of green coffee beans is an important process in defining their quality and market price. This evaluation is normally carried out by visual inspection or using traditional instruments which have some limitations. Thus, the objective of this study was to construct a computer vision system that yields CIE (Commission Internationale d'Eclairage) L*a*b* measurements of green coffee beans and classifies them according to their color. Artificial Neural Networks (ANN) were used as the transformation model and the Bayes classifier was used to classify the coffee beans into four groups: whitish, cane green, green, and bluish-green. The neural networks models achieved a generalization error of 1.15% and the Bayesian classifier was able to classify all samples into their expected classes (100% accuracy). Therefore, the proposed system is effective in classifying variations in the color of green coffee beans and can be used to help growers classify their beans.

1. Introduction

Color is an important attribute that is widely used to evaluate food quality and is a key factor in the market acceptance of food (Wu and Sun, 2013). Of the physical characteristics of green coffee beans, color has significant economic importance as discolored beans are associated with lower market prices (Borém et al., 2013). Although there are recent developments in coffee bean quality assessment, such as the analysis of hyperspectral images (Calvini et al., 2015; Backhaus et al., 2012), color remains a significant factor in the marketing of the product.

The CIE L*a*b*, an international color measurement standard adopted by the Commission Internationale d'Eclairage (CIE, 1986), has been used worldwide to measure food color because it has a uniform distribution and because it is a device-independent color space.

The tools traditionally used to measure color in CIE L*a*b*, such as colorimeters and spectrophotometers, normally only consider small and uniform surfaces. This limitation has generated the need to develop computer vision systems (Segnini et al., 1999; Papadakis et al., 2000).

In general, a computer vision system consists of a digital camera used to acquire images, a standard lighting system, and software for image processing and analysis (Brosnan and Sun, 2003; Wu and Sun, 2013). Quantitative information about color is extracted from digital images using image processing and analyzed for rapid and non-invasive color measurement. This method, which can be referred to as a digital colorimeter, is less expensive and more versatile than the use of traditional instruments to measure color (León et al., 2006).

Such systems have been widely adopted to rapidly quantify the color of various foodstuffs using low-cost equipment (Kumar et al., 2006; Valous et al., 2009; Mendoza et al., 2006; Segnini et al., 1999; Zhang, 2014). They have been applied in the analysis of beef (Larrain et al., 2008), pork (Sun et al., 2011), fish (Yagiz et al., 2009), orange juice (Fernandez-Vazquez et al., 2011), wine (Martin et al., 2007), beer (Sun et al., 2004), potato chips (Pedreschi et al., 2011), wheat (Zapotoczny and Majewska, 2010), bananas (Mendoza and Aguilera, 2004), and coffee beans (Sanz-Uribe et al., 2008).

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The color of green coffee beans can vary widely, which makes their classification by visual inspection difficult. Therefore, the objective of this study was to develop a computer vision system to measure the color of green coffee beans in the CIE L*a*b* color space and to classify them according to the Specialty Coffee Association of America (SCAA) and the Brazilian Official Classification (COB) methodologies.

This paper contributes to current research in the field by providing a method to construct a transformation model that converts device-dependent RGB (Red Green Blue) color space used by a digital camera to the device-independent CIE L*a*b* color space using Artificial Neural Networks (ANNs) (Haykin, 2009). Further, we propose a pattern recognition system to classify green coffee beans based on their measured CIE L*a*b color units using a Bayesian classifier (Mitchell, 1997). Finally, we assess the relationship between the green coffee bean color class and its measured CIE L*a*b* color units.

2. Materials and methods

2.1. Coffee samples

Our sample consisted of green beans of commercial Arabica coffee (*Coffea arabica* L.) harvested in 2013, provided by coffee growers from Minas Gerais State, Brazil. Using the SCAA and COB methods, we selected 120 50 g samples (30 per color) of the following color groups: whitish, green, cane green, and bluish-green. These color classes correspond to the colors most used commercially.

2.2. Computer vision system

The computer vision system developed in this study consisted of:

- A dark metallic chamber that minimizes background light and eliminates interference from outside light (Fig. 1).
- A Canon Powershot G12 digital camera with 10 megapixels resolution installed 40 cm above the sample plane, with the following settings: no flash use, fluorescent white balance, f/6.0 aperture, 1/10-s exposure, and ISO 160 speed.
- An intense white lighting system with two LED tube lamps (57 cm in length) of three Watts each and color temperature of 6500 K. The lamps were placed 40 cm above the samples at an angle of 45° to the sample plane giving a uniform light intensity over the coffee bean samples.
- A personal computer and software to analyze and process the images.

Images were taken at the maximum resolution of the digital camera (10 megapixels), and saved in Canon's raw image (.CR2) file format. The Digital Photo Professional® software (©CANON INC. 2005) was used to convert raw images to the widely used and readily interpreted tagged image file format (TIFF), with a resolution of 16 bits per channel in the RGB color space. This process provided 65,536 color unit intensities per pixel per channel. The images were cropped using the open source software ImageJ®. Cropping the image was necessary in order to select the part of the image that contained the samples since the image taken included background. All images were cropped to the same size.

2.2.1. *The transformation model*

The CIE L*a*b* color space uses the following spatial coordinates in the Cartesian system: (i) L* or luminescence, related to the grade of a material's shade, ranging from 0 (black) to 100 (white); (ii) a*, the red–green axis, ranging from −120 to 120; and (iii) b*, the blue–yellow axis, ranging from −120 to 120.

As the digital image obtained in RGB is affected by various factors, such as lighting and digital camera parameters, the direct conversion from RGB to the CIE L*a*b* color space is not possible. Thus, it is necessary to build a color space transformation model as discussed by León et al. (2006).

The methodology used in this paper to define the transformation model is described in Fig. 2. The following six steps were taken:

1. Select color charts: we constructed a dataset of 564 color chart samples in order to obtain a wide range of color unit values and to ensure the colors of coffee bean samples used in this study were included. Some samples are shown in Fig. 3.
2. Measure the CIE L*a*b* values of each color chart using a Minolta CR 400 colorimeter (CIE illuminant D65, color temperature of approximately 6500 K, 2° CIE, 1986 Standard Observer, data from calibrated white plate L*(97), a*(0.25), and b*(1.78)): we measured the CIE L*a*b* values of each color chart in triplicate and averaged the measurements to obtain final values. The

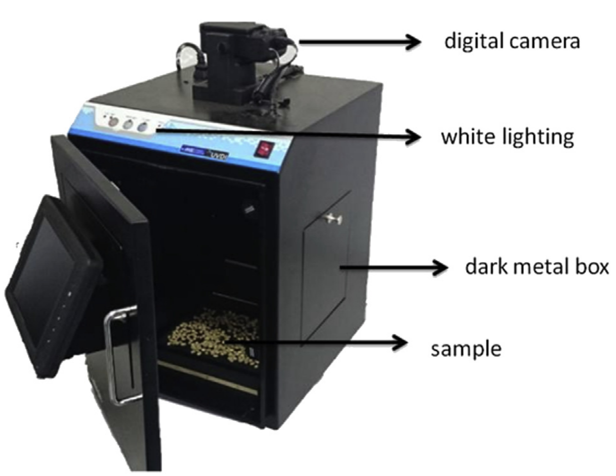

Fig. 1. Image acquisition system developed to classify coffee beans.

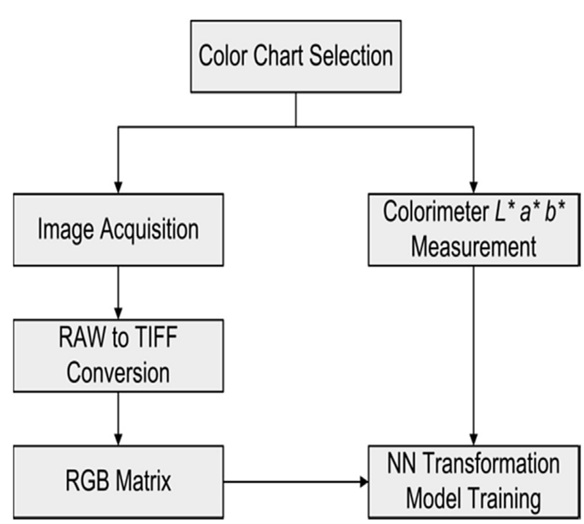

Fig. 2. Steps used to build the RGB–CIE L*a*b* transformation model.

Fig. 3. Examples of color charts used to define the transformation model. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

ranges of the measured values were approximately: $22 \leq L^* \leq 94$, $-54 \leq a^* \leq 9$, and $-13 \leq b^* \leq 50$.

3. Take pictures of the color charts using the digital camera in raw format.
4. Convert the acquired images to TIFF 16-bit format using the Digital Photo Professional® software and resize them using ImageJ®.
5. Read the TIFF images using the MATLAB® program which returns a three-dimensional matrix for each image corresponding to the RGB color space.
6. Define the transformation model using MATLAB®: the mean RGB values of each color chart are used as model inputs, and the respective CIE L*a*b* values provided by the colorimeter are used as outputs.

Transformation models can have various structures, including linear and non-linear polynomial models, with parameters estimated by the least squares algorithm (Sõdestrõm and Stoica, 1989), direct transformation models (Hunt, 1991), and non-linear models based on computational intelligence techniques like the ANNs (Haykin, 2009). We used ANNs in this study as they are universal function approximators (Cybenko, 1989) and they have been successfully applied as transformation models in other studies (León et al., 2006).

A *Multi Layer Perceptron* feed-forward ANN, composed of a hidden layer of five neurons with non-linear activation function (hyperbolic tangent) and one linear output neuron, was trained using the Levenberg–Marquardt algorithm with the early-stopping procedure (Haykin, 2009). We built three distinct neural networks, one for each output (CIE L*, a*, or b*), as shown in Fig. 4. The ANN parameters were obtained using the Neural Network toolbox in MATLAB®.

The dataset of 564 color chart images was randomly divided into two datasets: training dataset (80% of samples) and validation dataset (20% of samples). To define the ANN structure (i.e., number of hidden nodes, number of training epochs, non-linear activation function), we conducted 500 repetitions of the holdout cross-validation procedure (Bishop, 1996). To test network generalization, we used the validation datasets.

The network error was evaluated using the following criterion (León et al., 2006):

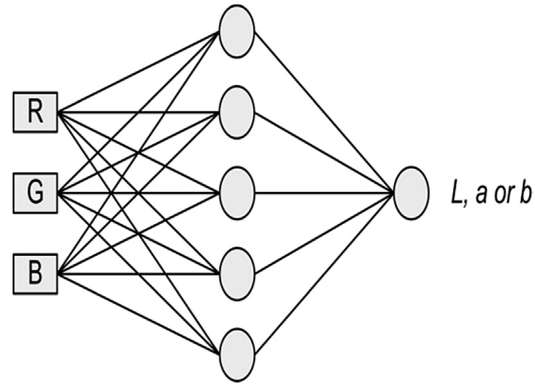

Fig. 4. Structure of the three artificial neural networks (ANN) used to transform RGB to CIE L*a*b* color spaces. Each ANN yields one of the CIE L*a*b* color units as output.

$$\bar{e} = \frac{e_L + e_a + e_b}{3}, \tag{1}$$

where:

$$e_L = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|L_i^* - \widehat{L}_i\right|}{\Delta L}, \tag{2}$$

$$e_a = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|a_i^* - \widehat{a}_i\right|}{\Delta a}, \tag{3}$$

$$e_b = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|b_i^* - \widehat{b}_i\right|}{\Delta b}, \tag{4}$$

and ΔL, Δa, and Δb refer to the lengths of variation intervals for CIE L*a*b* components ($0 \leq L^* \leq 100$, $-120 \leq a^* \leq 120$, and $-120 \leq b^* \leq 120$); that is, $\Delta L = 100$ and Δa, $\Delta b = 240$, and N is the number of observations.

2.3. Pattern recognition system

Images of the green coffee beans from the four color classes (whitish, green, cane green, and bluish-green) were obtained by placing the beans on a black surface in the dark chamber with the convex sides facing up (Fig. 5a). The black background of the acquired images was then removed using a segmentation process based on the conversion of the color image to a grayscale one and on the selection of a threshold. The threshold was defined for this specific setup of lighting and background by analyzing the histogram of the grayscale images and through trial-and-error. We selected only one threshold for all images. As such, RGB matrixes corresponding only to the color of the coffee beans were obtained (Fig. 5b). These matrixes were converted to the CIE L*a*b* color space using the trained ANN transformation model.

2.3.1. The Bayesian classifier

After obtaining the CIE L*a*b* color values for the green coffee beans, we used a pattern classification tool to recognize the color group of the coffee samples. Despite the many classifiers that could be used to accomplish this task, we decided to use the Naive-Bayes classifier which is simple, fast, robust, easy to understand and easy to interpret.

The Bayesian classifier learns probability distributions from data

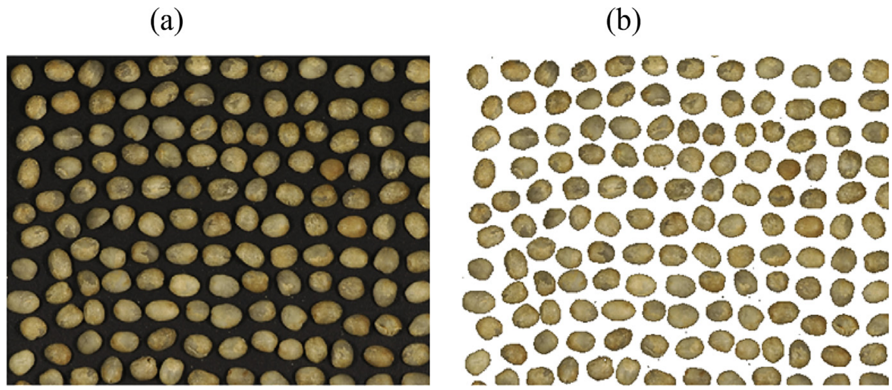

Fig. 5. Image acquisition and pre-processing of coffee beans samples: (a) image without pre-processing; (b) image after removal of the black background.

and classifies a test instance, x, by choosing the class with the maximum a posteriori probability (MAP) (Mitchell, 1997). The class is chosen to satisfy:

$$\mathscr{H}_{MAP} = arg_{\mathscr{H}i \in \mathscr{H}} \max p(x/\mathscr{H}i)p(\mathscr{H}i), \tag{5}$$

where $p(\mathscr{H}i)$ is a priori probability and $p(x/\mathscr{H}i)$ is the conditional probability density function of class $(\mathscr{H}i)$ where x is the attribute value (CIE L*a*b* color units), and $i = 1, 2, 3$, and 4, corresponding to the four color classes identified for this study: whitish, cane green, green, and bluish-green.

Considering that the Naive-Bayes classifier assumes independence between features, the conditional probability density function based on the Gaussian distribution is expressed as:

$$P(x/\mathscr{H}i) = \prod_{k=1}^{3} P(x_k/\mathscr{H}i), \tag{6}$$

$$p(x_k/\mathscr{H}i) = \frac{1}{\left(2\pi\sigma_{ik}^2\right)^{\frac{1}{2}}} exp\left\{ -\frac{1}{2\sigma_{ik}^2} (x_k - \mu_{ik})^2 \right\}, \tag{7}$$

where $k = 1, 2$, and 3 (L*, a* and b*), μ_{ik} is the mean value of class $\mathscr{H}i$, and σ_{ik} is its variance.

Assuming uniform a priori probabilities,

$$\mathscr{H}_{ML} = arg_{\mathscr{H}i \in \mathscr{H}} \max p(x/\mathscr{H}i), \tag{8}$$

where $\mathscr{H}_{ML}$ is the Maximum Likelihood hypothesis.

In order to obtain the classifier parameters, we used the Statistics toolbox in MATLAB®.

3. Results and discussion

3.1. The transformation model

The average errors achieved by the ANN transformation model, after running 500 repetitions of the holdout cross-validation procedure, are presented in Table 1. The results obtained in this study are 1.20% ± 1.24% for the training set and 1.15% ± 1.01% for the validation set; these values are comparable to those reported by León et al. (2006) who found errors of 0.95% ± 1.28% for the training set and 0.87% ± 1.22% for the validation set. However, it is important to note that we used 564 color samples whereas only 32 color samples were used in the León et al. (2006) study. Since a wider range of color unit values was used in our study, it can be considered a more complex task, proving that the results obtained by the defined transformation model are comparable with those found by León et al. (2006).

According to CIE (1986), the difference between colors in the CIE L*a*b* space can be expressed as:

$$\Delta E_{ab}^* = \sqrt{(\Delta L^*)^2 + (\Delta a^*)^2 + (\Delta b^*)^2}. \tag{9}$$

The human eye can distinguish average ΔE_{ab}^* of 2.2 or even 4 units (Valous et al., 2009). The transformation models developed in this study reached 2.97 ΔE_{ab}^* units for test data, confirming that they were well estimated and can be used to analyze green coffee bean samples.

Table 1
Mean, ± standard deviation of error, obtained by the color space transformation models based on artificial neural networks (ANN).

	Training	Validation
$\boldsymbol{e_L}$(%)	2.33 ± 2.23	2.26 ± 1.96
$\boldsymbol{e_a}$(%)	0.63 ± 0.51	0.57 ± 0.43
$\boldsymbol{e_b}$(%)	0.64 ± 0.64	0.62 ± 0.60
$\hat{e}$(%)	1.20 ± 1.24	1.15 ± 1.01

3.2. The pattern recognition system

The converted CIE L*a*b* mean values of the green coffee bean samples are presented in Fig. 6. We can see that the color classes are linearly separated, which means the Naive-Bayes classifier achieves 100% of classification accuracy regardless of how the training/validation datasets are defined. Thus, we decided to use all available data (120 green coffee bean samples) to obtain the parameters of the Naive-Bayes classifier, μ_{ik} and σ_{ik} (Eq. (7)).

By analyzing Fig. 6 (b), we can see that only the color unit a* is needed to achieve 100% classification accuracy, because linearly separated classes would be still identified if only this parameter was considered. However, in order to make the classifier more robust and reliable, we decided to maintain the other two color units.

The mean values (μ_{ik}) of the Gaussian conditional probability density functions are shown in Table 2.

As can be seen in Table 2, the parameter L* was higher for the whitish samples (46.78) demonstrating a high whitening value, as expected since L* represents lightness. The cane green samples showed high values of L* (40.84) that are lower than the values obtained for the whitish samples, but higher than those found for the green or bluish-green samples. The green and bluish-green samples showed the lowest values of L*. According to Coradi et al.

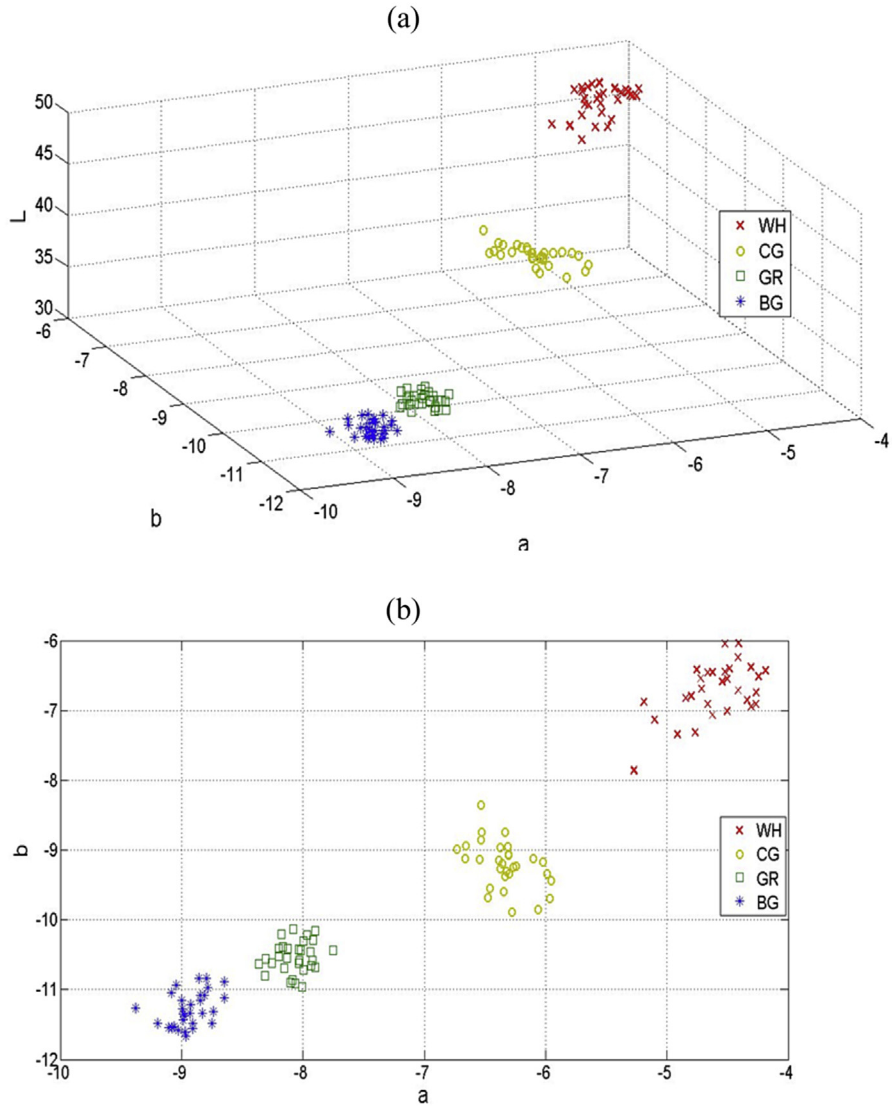

Fig. 6. CIE L*a*b* values of the green coffee bean samples (WH – whitish, CG – cane green, GR – green, and BG – bluish-green): (a) all three color units are shown; and (b) only a* and b* are shown. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

Table 2
Mean values (μ) of attributes (color units) for each class of the Naive-Bayes classifier.

	L*	a*	b*
Whitish	46.78	−4.62	−6.75
Cane Green	40.84	−6.35	−9.15
Green	32.83	−8.07	−10.56
Bluish-Green	32.49	−8.93	−11.27

(2007) and Ribeiro et al. (2011), CIE L*a*b* values increase with increased length of storage time, which is consistent with the findings found in our study. In Fig. 6, we can see that the values increase significantly from the bluish-green (best price) samples to the whitish (lowest price) samples. We can also note that the whitish class showed high values of the parameters a* (−4.62) and b* (−6.75) demonstrating a loss of green and blue colors, and presenting a color closer to yellow. On the other hand, the bluish-green class has lower a* (−8.93) and b* (−11.27) values than the other classes, which makes this class closer to green and blue, as expected. Therefore, higher CIE L*a*b* values are associated with green coffee beans of lower commercial value.

4. Conclusions

This study presents a computer vision system to analyze and classify green coffee beans based on computational intelligence techniques. The results show that the developed system allows us to precisely and objectively determine the color of coffee beans in the CIE L*a*b* color space. To do so, it was necessary to: *i.* Use a dark photo chamber with an appropriate lighting system; *ii.* Set-up the digital camera with the correct parameters; *iii.* Select color charts that represent colors close to those normally found in green coffee beans; and *iv.* Train the transformation model, composed of three Neural Networks, to convert from RGB to CIE L*a*b* color spaces.

After achieving reliable measurements of CIE L*a*b* values for green coffee beans, their classification became an easy task (linearly separated classes) and we obtained a classification accuracy of 100% using a Naive-Bayes classifier. Thus, the entire system developed herein is capable of distinguishing the colors of green coffee beans achieving results consistent with coffee experts who classify coffee beans using visual inspection.

The results also show the correlation between the green coffee bean classes and the CIE L*a*b* values, where higher values for color units suggest lower market value.

Finally, the computer vision system can be used by coffee growers to analyze green coffee beans and the method can be extended to other food industries enabling improved characterization of food and, consequently, improved food quality.

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