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## A feasibility cachaca type recognition using computer vision and pattern recognition



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#### ABSTRACT

Brazilian rum (also known as cachaça) is the third most commonly consumed distilled alcoholic drink in the world, with approximately 2.5 billion liters produced each year. It is a traditional drink with refined features and a delicate aroma that is produced mainly in Brazil but consumed in many countries. It can be aged in various types of wood for 1–3 years, which adds aroma and a distinctive flavor with different characteristics that affect the price. A research challenge is to develop a cheap automatic recognition system that inspects the finished product for the wood type and the aging time of its production. Some classical methods use chemical analysis, but this approach requires relatively expensive laboratory equipment. By contrast, the system proposed in this paper captures image signals from samples and uses an intelligent classification technique to recognize the wood type and the aging time. The classification system uses an ensemble of classifiers obtained from different wavelet decompositions. Each classifier is obtained with different wavelet transform settings. We compared the proposed approach with classical methods based on chemical features. We analyzed 105 samples that had been aged for 3 years and we showed that the proposed solution could automatically recognize wood types and the aging time with an accuracy up to 100.00% and 85.71% respectively, and our method is also cheaper.

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#### 1. Introduction

Brazilian rum is an alcoholic drink obtained from the fermentation of molasses and other derivatives of sugar production. Drinks such as whiskey, brandy, and wine are aged in oak barrels, but Brazilian rum uses different wood types in this process, such as amburana (*Amburana cearensis*), oak (*Quercus spp.*), and castanheira (*Bertholletia excelsa* H.B.K). Each wood has different effects during the aging process, which determine the color, odor, and taste characteristics of the drink.

Legislation classifies cachaca into three types: aged, premium, and extra premium. The difference among types is related to aging time and shelf life. Aged and premium have aging period of at least 1 year. Aged may contain up to 50% non-aged cacacha. Premium

\* Corresponding author. *E-mail address:* anderson@inf.ufg.br (A.S. Soares). has 100% aged cachaca. Extra premium has a minimum aging period of at least 3 years and cannot contain non-aged cachaca.

Despite the legislation, production can deviate from quality standards or can be fraudulent. Because of this, new technologies have been investigated to improve quality control. The development of a method to recognize the wood type and the aging time is important for preventing fraud and to enforce regulations related to the identification of the different types.

De Souza et al. (2006) and de Souza et al. (2007) uses gas chromatography to separate and characterize the odors in cachaca and rum. These two products of sugarcane were compared and patterns identified from a descriptive sensory analysis. The author used principal component analysis (PCA), a statistical approach in which data are represented by a subset of their eigenvectors. His work contributed to further studies that use this technique for the identification of artisanal and industrial cachaca as well as the detection of adulteration by adding caramel and other substances such as dyes. The disadvantage of this method is that it differentiates between cachacas and rums using mass spectrometry, which is difficult to maintain because of its high cost.

Recent works use techniques of computer vision, neural networks, genetic algorithms, and statistical methods for food and drink classification (Kongsro, 2014; Kashiha et al., 2014; Fernán dez-González et al., 2014; Kashiha et al., 2013; Rodríguez-Pulido et al., 2013). Duarte-Mermoud et al. (2010) proposed a method based on Quadratic Discriminant Analysis (QDA) for wine recognition, where features were extracted from liquid chromatograms (based on a diode alignment detector) of polyphenolic compounds present in wine samples. Near-infrared spectrometry and chemometric methods for classification were applied successfully by Pontes et al. (2006) to verify the adulteration of whiskey, brandy, rum, and vodka. The characterization of drinks was accomplished by chemometric models based on classification methods. According to Pathare et al. (2013), alternatives to chemometric techniques include the use of a colorimeter, which is a light-sensitive instrument that measures how much color is absorbed by an object or substance. Recently, Rodrigues et al. (2014) showed that colorimeters can obtain useful information about types of Brazilian rum. However, chemometric and colorimetric approaches are expensive in actual practice.

In this paper we propose a relatively cheap system based on visual color information for the recognition of wood type and aging time. The system comprises a capture device and software that processes and classifies samples using color features. The image is captured by a traditional additive color model (RGB), which uses the primitive colors red (R), green (G), and blue (B) to reproduce a broad array of colors (Gevers et al., 2012). The RGB color model is not efficient for representing perceptual color distances in real-world images. RGB components have the same color depth and not all colors can be represented as a combination of primitive colors (Gevers et al., 2012). In addition, luminance (*luma*) and color (*chroma*) information is distributed in the R, G, and B components, which can complicate wood type recognition.

The proposed system transforms the images captured from RGB into the CIE 1976  $L^*a^*b^*$  color model, which separates perceptual lightness information  $(L^*)$  from color opponent information  $(a^*)$ and  $b^*$ ) (Reinhard et al., 2008). This model is a non-linear compression of tristimulus CIE 1931 XYZ color space that achieves a perceptual uniformity and enables computing perceptual color differences using Euclidean distance. Due to more uniform color perception representation, the CIE  $L^*a^*b^*$  color space is more suitable for perceptual color metrics (Reinhard et al., 2008). The differences in the perceptual white intensity of samples can be standardized by converting RGB data into the  $L^*a^*b^*$  format by removing the lightness  $(L^*)$  component. This correction reduces the effect of variations in lightness contrast on the color features of samples. Next, an ensemble based on the Adaptive Boosting (AdaBoost) algorithm is carried out on images decomposed by wavelet transforms. The proposed method consists of generating an ensemble model as a combination of images with different resolutions over the same sample. The images of different resolutions are obtained by using different wavelet transform settings in a way similar to that proposed by Pinto et al. (2010). It has been reported that the ensemble model is often more accurate than its individual classifiers (Schaefer et al., 2014; Sujatha et al., 2013; Yu et al., 2012). The final result is obtained by co-averaging the results of the individual classifiers.

#### 2. Proposed system

The proposed approach is a typical computer vision system with a hardware device for image capture, an information processing method for feature extraction using wavelet coefficients, and a classifier ensemble for making the final decision required for the application. Each component is describe in the following subsections.

#### 2.1. Hardware device

The proposed system comprises a capture device and intelligent software that assigns input signals to the correct wood type and ageing time. Fig. 1 shows our capture device. The samples are photographed with a digital camera (Canon EOS REBEL XS) with the ISO 100 configuration, an aperture of 4.0 mm, and image format set to RAW. The light used to photograph the samples is given by a fluorescent lamp (40 W and 6400 K color temperature), which enables the incidence of light to be controlled in the direction opposite to the camera lens. A special 3 mm filter with nonreflective white acrylic prevents reflections in the liquid, thereby producing a digital image that is suitable for computational processing. The light control device located on the sides and at the top is built from wood painted with matte black paint.

An image collected in the RGB color model is converted into the  $L^*a^*b^*$  color model. The color conversion is performed from RGB to XYZ and finaly to CIE  $L^*a^*b^*$  color space considering CIE standard illuminant D65 as described by Gevers et al. (2012). The  $L^*$  component is expressed as continuous lightness from 0 for black to 100 for white. The color opponent dimensions,  $a^*$  and  $b^*$ , range from greenish to reddish and from bluish to yellowish respectively in a continuous and unbounded range of values. In the proposed approach, the lightness component is removed from the samples to reduce interference caused by variations in lightness.

#### 2.2. Information processing

Fig. 2 presents the basic schema proposed in this paper. It consists of wavelet decomposition filter banks with low-pass and high-pass filters, each followed by a downsampling operation  $(\downarrow 2)$ . Wavelets are defined by a wavelet function  $\psi(t)$  (also called a mother wavelet) and a scaling function  $\phi(t)$  (also called a father wavelet) in the time domain. The low-pass filter is associated with the father wavelet while the high-pass filter is associated with the mother wavelet (Mallat, 1999). The wavelet filter banks contain a collection of images of decreasing resolution. The first level has the highest resolution while the last level has the lowest.

The choice of the mother wavelet was made empirically (Mallat, 1999; Petrosian and Meyer, 2013). The filter bank was tested with different mothers wavelets of the Daubechies (db), and Symlet (sym) families, which are commonly used in image analysis. Overall, 10 filters were employed (db2-db6 and sym4-sym8).

In Fig. 2(b), each low pass filter result is reapplied to the results of the others to obtain new images at higher levels, i.e., with lower resolution. The input features for the classifiers are the wavelet coefficients in each decomposition level. The multilevel decomposition provides the information about frequency components present and enhance the information about the images. The first level contain high frequencies. The patterns are generally hardly



Fig. 1. Capture device.

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