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Neuro-fuzzy model based on digital images for the monitoring of coffee bean color during roasting in a spouted bed

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ABSTRACT

An adaptive-network-based fuzzy inference system based on color image analysis was used to estimate coffee bean moisture content during roasting in a spouted bed. The neuro-fuzzy model described the grain moisture changes as a function of brightness (L^*), browning index (BI) and the distance to a defined standard (ΔE). An image-capture device was designed to monitor color variations in the $L^*a^*b^*$ space for high temperatures samples taken from the reactor. The proposed model was composed of three Gaussian-type fuzzy sets based on the scatter partition method. The neuro-fuzzy model was trained with the Back-propagation algorithm using experimental measurements at three air temperature levels (400, 450 and 500 °C). The performance of the neuro-fuzzy model resulted better compared to conventional methods obtaining a coefficient of determination > 0.98, a root mean square error < 0.002 and a modified Schwarz–Rissanen information criterion < 0. The simplicity of the model and its robustness against changes in the input variables make it suitable for monitoring on-line the roasting process.

1. Introduction

Coffee, obtained from grounded and roasted beans is one of the most consumed beverages worldwide, and it is considered as the second most valuable commodity just after oil (Bae, Park, Im, & Song, 2014). It was estimated that during the year 2015/2016 the total production of coffee by all exporting countries would reach to 152.2 million expressed as 60 kg bags (USDA, 2015). The moderate consumption of this drink has been related to the reduction of chronic diseases such as Type 2 Diabetes Mellitus, Parkinson's and liver Disease (Higdon & Frei, 2006).

Drying and roasting are two important processes related to coffee. Moisture promotes fungal contamination in the green coffee having effect on the taste and smell of the final product (FAO, 2006). It is less probably that a microorganism like fungi grows and produces toxins in low water content; consequently preserving the seed for longer time. Therefore, drying is a proper procedure to reduce the moisture from the harvested green coffee for this purpose sun and mechanical dryers have been used (Ghosh & Venkatachalapathy, 2014). Roasting is the second relevant process, in which the coffee obtains its organoleptic characteristics. Drying is also the first step in roasting, in this stage the coffee bean losses an important amount of water. Later during the roasting or pyrolysis phase the temperature increases up to 260 °C. In this step coffee produces its characteristic aroma and flavor by the action of diverse chemical reactions (Buffo & Cardelli-Freire, 2004). Finally, rapid cooling is necessary to halt the reactions. At the end of the roasting process, the bean has lost almost 90% of the initial moisture (Baggenstoss, Poisson, Kaegi, Perren, & Escher, 2008).

On the other hand in roasting, the temperature transferred to the coffee bean has straight effect on the final product so that this parameter needs to be monitored and controlled. However, the quality of the roasted coffee will be the result of the moisture loss, the density, pH, the gas composition, the volume, the bean pop and form, the volatile components produced and the change in color during the process (Bottazzi, Farina, Milani, & Montorsi, 2012). Significant variability can be often found in the final roasted coffee, which might be caused by the diversity in

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Nomenclature

ΔE	Geometrical distance between colors (–)
a^*	CIE red(+)/green(−) color attribute (–)
b^*	CIE yellow(+)/blue(−) color attribute (–)
BI	Browning index (–)
c	Modal value of a fuzzy set (–)
f	Function defined by equation 8 (–)
k_1	Kinetic constant defined by equation 12 min^{-1}
k_2	Kinetic constant defined by equation 13 min^{-1}
L^*	CIE lightness coordinate (–)
m	Number of parameters (–)
N	Number of data points (–)
p	Consequent parameter (–)
q	Consequent parameter (–)
r	Consequent parameter (–)
RGB	Red, green and blue (–)
s	Consequent parameter (–)
T	Temperature °C
w	Weighted parameter for each node (–)
x	Parameter define by equation 2 (–)

Sub-indexes

0	Initial
A	Air
a	Antecedent
c	Consequent
i	Sample
p	Fixed standard or particle
r	Fuzzy rules

Greek letters

μ	Membership function
σ	Dispersion of a fuzzy set
$\sigma^2{}_e$	Estimated variance of the errors

the raw material (Hernandez, Heyd, Irles, Valdovinos, & Trystram, 2007, Severa, Buchar, & Nedomová, 2012). Moreover, most of the quality imperfections of coffee are produced by inadequate control of the drying process (Murthy & Naidu, 2012). This could be due to the uncertainty in the operational conditions; since this process is frequently empirically controlled. Another cause is the highly non-linear dynamics present in food processes (Perrot et al., 2006), and the scarce knowledge of the phenomenon arising inside the roaster. In addition, inadequate roasting of coffee can produce carcinogenic compounds, such as polycyclic aromatic hydrocarbons (Orecchio, Ciotti, & Culotta, 2009).

It is quite difficult to measure on-line the parameters that can determine the quality of the roasted coffee. Nevertheless, one of the most convenient parameter to associate the degree of roasting is the color. The color of the bean relates to the final roasting temperature (Buffo & Cardelli-Freire, 2004), the higher the temperature, the darker the coffee, so that color can be used to define the end point operation. Changes in color are mainly due to the thermal decomposition and pyrolysis of organic compounds accompanied by dry distillation. The relation between the color and some characteristic compounds produced during the roast has been studied (Şenyuva & Gökmen, 2005). Computer vision is used in food science to objectively measure color differences. A detailed characterization for food image products will require being aware of the color value for each pixel. However, commercial colorimeters determine color values only within a limited region i.e. 2 cm^2, so their measurements are not representative of heterogeneous materials such as food (Segnini, Dejmek, & Öste, 1999), in addition it is not possible to determine the color at surface temperatures above 80 °C. It has been reported that color-based procedures in roasting using conventional methods have proven to be ineffective (Dutra, Oliveira, Franca, Ferraz, & Afonso, 2001, Edzuan, Aliah, & Bong, 2015) since coffee beans roasted to different degrees can present the same average readings.

Describing the input-output relationships in a drying process by means of numerical techniques is quite complex (Aghbashlo, Mobli, Rafiee, & Madadlou, 2012). Recently, tools from the Artificial Intelligence such as Artificial Neural Networks (ANN) and Fuzzy Logic have been used in the drying process. Fuzzy logic was introduced by Lofti Zadeh (Zadeh, 1965). In a fuzzy system the experience obtained from the human process operator is used to build linguistic IF-THEN rules that along with membership functions and the inference mechanism can model a process without the need of complex mathematical models. Fuzzy logic has been used to model and control drying processes (Aghdam et al., 2015, Brown, Rothwell, & Davidson, 2001, Yliniemi, Koskinen, & Leiviskä, 2003). On the other hand, ANN are well suited to model the non-linear dynamics of uncertain and noisy systems learning from historical data. ANNs have been used to predict kinetics, moisture content, texture properties, in the drying process (Aghbashlo, Hosseinpour, & Mujumdar, 2015; Menlik, Özdemir, & Kirmaci, 2010; Ttayagarajan, Ponnavaikko, Shanmugam, Panda, & Rao, 1998). Roasting is more complex than drying because several chemical reactions are given during this process. Compared to drying, there are fewer artificial intelligence applications in roasting. For instance, ANN and electronic nose have been used to predict different coffee roasting degrees with good accuracy (Romani, Cevoli, Fabbri, Alessandrini, & Dalla Rosa, 2012). However, the use of ANN in drying/roasting processes is hampered by the difficulty in choosing the proper structure and algorithm of the net. The adaptive-network-based fuzzy inference system (ANFIS) merge the advantages of ANN and fuzzy logic into a unique system, and has proven to have potential in drying systems performing better than ANNs (Aghbashlo et al., 2015). Nevertheless, more knowledge is required to overcome the limitations shown during coffee drying and roasting, especially the difficulties in coffee color image analysis based in conventional measurements and colorimeters. In addition, it is desirable to have fast techniques allowing the estimation of variables, such as the moisture content, that are closely related to the roasting degree (Bottazzi et al., 2012). Therefore, in this manuscript it is proposed an ANFIS to estimate moisture content as an approach to determine coffee roasting degree based on color image analysis. ANFIS overcomes the technical difficulties of using commercial colorimeters and the conventional color instruments to detect color changes during the roasting process. The manuscript is organized as follows: the next section gives a brief background on ANFIS. Section 3 shows the experimental methodology and the results, and discussion are given in Section 4. Finally, the conclusions and future work are stated.

2. ANFIS background

Fuzzy logic and ANN are tools from the intelligent systems that have had diverse applications in the drying process. Nevertheless, for a ANN it is difficult to choose the proper structure and algorithm and in a fuzzy system it is sometimes complex to convert the human experience or human knowledge into fuzzy rules; as well, it is difficult tuning the membership functions in such way that minimize the error in the fuzzy model. The adaptive-network-based fuzzy inference system (ANFIS) was proposed to solve the problems previously mentioned (Jang, 1993). Neural fuzzy systems combines the learning and capability connections of ANN to the human-like reasoning of fuzzy systems (Kar, Das, & Ghosh, 2014). ANFIS has been used in image analysis, process control and forecasting modeling, among many other applications (Kar et al., 2014).