Feasibility of computer vision as Process Analytical Technology tool for the drying of organic apple slices

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Abstract

Quality of a product and sustainability of its production depend on the cumulative impacts of each processing step in the food chain and their interplay. Various research studies evidenced that many drying systems operate inefficiently in terms of drying time, energy demand (e.g. fossil fuels), raw material utilisation and resulting product quality. Moreover, not all conventional drying processes are allowed in the organic sector (Reg. EC 834/2007; Reg. EC 889/2008).

In recent years, non-invasive monitoring and control systems have shown a great potential for improvement of the quality of the resulting products. Thus, there is a need for smart processes which allow for simultaneous multi factorial control to guarantee high-value end products, enhance energy and resource efficiency by using innovative and reliable microcontrollers, sensors and embracing various R&D areas (e.g. computer vision, deep learning, etc.). The objective of this study was to evaluate the feasibility of computer vision (CV) as a tool in development of smart drying technologies to non-destructively forecast changes in moisture content of apple slices during drying. Usage of computer vision (CV) as Process Analytical Technology in drying of apple slices was tested. Samples were subjected to various anti-browning treatments at sub- and atmospheric pressures, and dried at 60°C up to a moisture content on dry basis (MC_{db}) of 0.18 g/g. CV-based prediction models of changes in moisture content on wet basis (MC_{wb}) were developed and promising results were obtained ($R^2P > 0.99$, RMSEP = 0.011÷0.058 and BIASP < 0.06 in absolute value), regardless of the anti-browning treatment.

The proposed methodology lays the foundations for a scale-up smart-drying system based on CV and automation.

Keywords: image analysis; dipping treatments; vacuum impregnation; chemometrics; smart drying

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INTRODUCTION

Consumers in developed countries are becoming more critical and demanding in their food choices (Grunert *et al.* 2005); they expect high-quality foods produced sustainably and preferably regionally. In addition, European policy pushes towards the sustainable development of the food sector through mid- and long-term goals. Up to the year 2050, food industry will face three important challenges: (i) to meet the global food demand generated by a growing population (ii) to increase the sustainability of the food sector and (iii) to meet consumer expectations of quality and safety.

Processing methods that enhance food stability and retain food quality have an enormous impact in globalized market through the reduction of food losses and processing, storage, transportation and distribution costs (Moscetti *et al.* 2017). In this context, food drying plays a major role because it is successfully used to reduce storage and shipping costs by enabling storage at room temperature, reducing weight and packaging volume. Despite these advantages, drying is one of the most energy-intensive processes in the food industry; in fact, it potentially contributes to climate change as most dryers use fossil fuels (Moscetti *et al.* 2018a). Moreover, drying usually requires long process cycle times and may negatively affect physicochemical and sensorial characteristics of the final product (Raponi *et al.*, 2017; Ratti, 2001). In order to alleviate drying drawbacks, several studies were carried out over the years with the aim of increasing the process efficiency through development and optimization of (i) heat recovery systems (Barbosa de Lima *et al.* 2015; Kemp, 2005), (ii) pre-processing methods of raw material to be dried (Lukinac, 2013) and (iii) real-time monitoring and control systems of process parameters affecting quality of the end-product (Sturm *et al.* 2014; Winiczenko *et al.* 2018).

Among emerging drying technologies, smart drying is one of the recent and most promising techniques (Moscetti *et al.* 2018a). It enables to proactively monitor quality changes in product as well as dryer operating conditions, through an interdisciplinary approach which involves various scientific sectors, such as chemometrics (Pomerantsev and Ye, 2012), artificial intelligence (Sun et al., 2018), biomimetics (e.g. electronic nose, tongue and mucosa) and computer vision (Sturm et al., 2014) as well as single-point spectroscopy and hyper/multi-spectral imaging (Moscetti *et al.* 2018a).

Apple is the fourth most consumed commercial fruit worldwide (Aghilinategh *et al.* 2015) and due to the modern lifestyle, dried apple exhibits a growing trend in consumption as snacks, chips or integral breakfasts (Vega-Gàlvez *et al.* 2012). However, hot-air drying of apple may result in discolouration due to browning reactions (Sturm et al., 2012). Thus, pre-treatment of raw material is strictly recommended in order to produce a high-quality end-product. However, pre-treatment may affect drying kinetics and subsequently impact the modeling of thin-layer behaviour of product, which is fundamental in deciding the ideal drying conditions (i.e. equipment design, optimization and product quality improvement).

The objective of this study was to evaluate both feasibility and robustness of computer vision as Process Analytical Technology tool for modeling the drying kinetics of apple slices subjected to various anti-browning treatments.

MATERIAL AND METHODS

Sound apples (*Malus domestica* Borkh var. Gala) at the same ripening stage were washed, peeled, decored and cut into slices of 5-mm thick and 23-mm diameter. Samples were (i) dipped in trehalose 4% w/v (TR); trehalose 4% w/v + ascorbic acid 1% w/v (TR+AA); and water as control (CNT) at atmospheric and subatmospheric pressure (i.e. vacuum impregnation, VI); and then (ii) dried at 60°C up to a final MC_{db} of 0.18 g/gDW. Ascorbic acid was selected due to its well-known inhibition effect towards polyphenol oxidase (Albanese *et* *al.* 2007; El-Shimi, 1993). Trehalose is a natural disaccharide, generally recognised as safe (Megarry *et al.* 2011), used as a food ingredient and pharmaceutical excipient. It acts as an edible coating with ability to preserve colour and aroma of the dried fruits as well as reduce non-enzymatic browning occurrence (Aktas et al., 2007; Albanese et al., 2007). Finally, subatmospheric pressure (i.e. VI) was tested because of its potential in stabilizing functional properties of food and its higher capability of embedding fruit and vegetable tissues with solutes when compared with conventional dipping (Neri et al., 2016).

The relative humidity of the drying process was not controlled but measured. Treatments were carried out at 20°C for a dipping time of 5.25 min, with a sample/solution ratio of 1:5 (w/w); specifically VI treatment consisted of a 0.25 min vacuum time and a 5 min post-vacuum time, and was achieved using a 5-L vacuum chamber connected to a vacuum pump mod. N 840.3 FT.18 (KNF, USA). Drying was performed using a hot-air dryer mod. Biosec (Tauro Essicatori, Italy) which was ad-hoc modified to embed a digital balance mod. HT1500 (NHU, Germany), a camera mod. EOS 400D (CANON, Japan) and a 4200K illuminant source. The drying setup was controlled using a single-board computer mod. Raspberry Pi B+ (Raspberry Foundation, UK) in combination with a self-made Jupyter Notebook (Project Jupyter, USA), which allowed (i) to collect data at constant time intervals (i.e. image and weight of samples every 5 min and 4 sec, respectively) and (ii) to extract morphological feature of samples from each raw image (i.e. surface area of samples). The 'relative area shrinkage' was calculated according to Eq. 1:

$$S_b = \frac{S_t}{S_0} \qquad (1)$$

where S_b corresponds to the 'relative area shrinkage', S_t represents the 'surface area' in pixels at the drying time '*t*', and S_0 corresponds to the 'surface area' in pixels of the fresh sample. The R software v3.4.1 was used to develop linear prediction models able to relate the changes in MC_{wb} of apple slices to the changes in relative area shrinkage during drying. Model performances were evaluated in terms of Root Mean Square Error (RMSE), BIAS and coefficient of determination (R^2) of calibration (Cal.) and prediction (Pred.).

RESULTS AND DISCUSSION

Changes in quality attributes of horticultural products during drying are successfully measurable based on their variations in spatial distribution data (i.e. size and shape information), which can be analysed through a computer vision system (Moscetti *et al.* 2018b). Consequently, we explored the possibilities offered by image analysis for quantifying the moisture content of apple slices as a function of change in the relative area shrinkage (S_b) of product during drying. As found in literature (Aghbashlo *et al.* 2016), the wet-basis moisture content (MC_{wb}) was successfully predicted using spatial information only. Thus, the additional value of the present work lays in the fact that these results underline the possibility of developing a forecast model for prediction of the drying time required by the product to reach a specific moisture content based on the past and present spatial data.

In general, Table 1 shows excellent results in terms of prediction capability, regardless of the anti-browning pre-treatments used. Results show a RMSEP ranging from 0.011 to 0.058 g/gFW, a BIASP lower than 0.06 in absolute value, and a R^2P always higher than 0.99. In addition, considering that the relative humidity (R.H.) of process was not controlled, it is possible to assert that all models were insensitive to the R.H. of the drying chamber.

Specifically, it is important to highlight that models computed using spatial data from samples subjected to VI had lower predicting performances and, were less robust. This is probably because apple is a highly porous product and VI alters both porosity and texture in a non-systematic way. However, further research would be necessary for verification.

Table 1. Summary of performance metrics of the linear regression models.

Dipping solution	VI[a]	RMSE[b]		BIAS[c]		R^{2d}	
		Cal.	Pred.	Cal.	Pred.	Cal.	Pred.
CNT[e]	No	0.009	0.019	$-2.98\ 10^{-17}$	-0.008	0.998	0.993
TR[f]	No	0.014	0.017	$-1.15\ 10^{-17}$	0.007	0.997	0.996
TR+AA[g]	No	0.008	0.022	$1.59\ 10^{-17}$	0.004	0.999	0.997
CNT	Yes	0.008	0.058	$-1.79\ 10^{-17}$	-0.055	0.999	0.999
TR	Yes	0.010	0.051	$-2.64\ 10^{-17}$	-0.049	0.998	0.999
TR+AA	Yes	0.005	0.011	$1.33\ 10^{-17}$	-0.041	1.000	0.999

[a]VI: Vacuum Impregnation (Yes and No stay for sub-atmospheric and atmospheric pressure, respectively).
[b]RMSE: Root Mean Squared Error of calibration (Cal.) and prediction (Pred.).
[c]BIAS: difference between the moisture content's expected value and the true value of the moisture content.
[d]R^2: coefficient of determination of calibration (Cal.) and prediction (Pred.).
[e]CNT: control (i.e. water dipping solution).
[f]TR: trehalose 4% w/v aqueous dipping solution.
[g]TR+AA: trehalose 4% w/v + ascorbic acid 1% w/v aqueous dipping solution.

Figure 1 shows results from the regression model for the TR+AA dipping treatment (no VI), which was selected as example treatment. For all models, a BIAS issue was evident during the second falling rate drying period, i.e. when MC_{wb} dropped below 0.1 g/gFW.

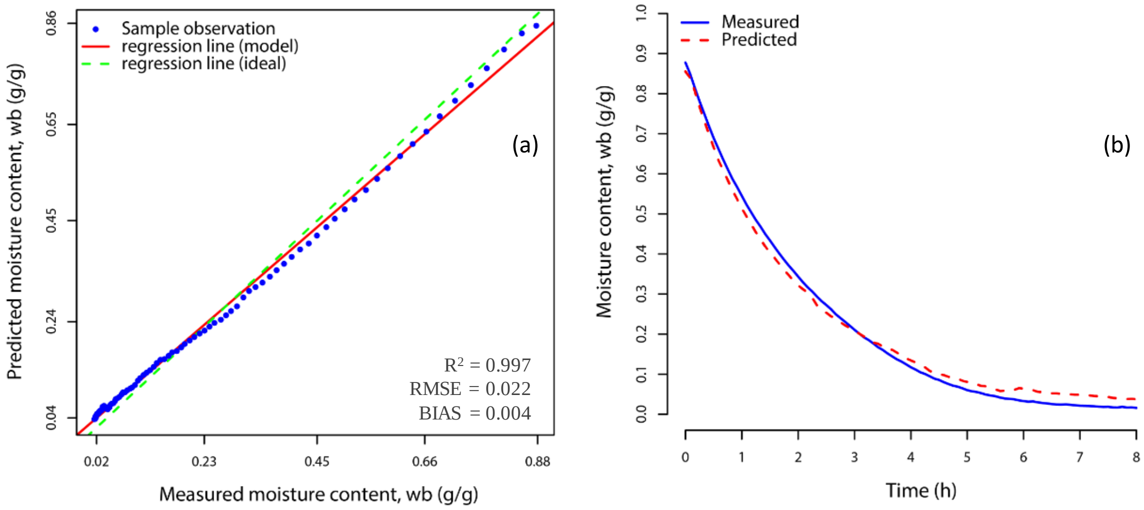

Figure 1. Linear regression plot (a) and first-order plot (b) of measured and predicted MC_{wb} values for the TR+AA dipping treatment performed at atmospheric pressure.

CONCLUSIONS

In this study the feasibility of using computer vision technology as smart-drying technology, to proactively and non-destructively detect and monitor physicochemical changes (i.e. moisture content) in organic apple slices (*Malus domestica* Borkh var. Gala) during hot-air drying at 60°C was investigated. The work represents a preliminary study for the development of large-scale CV-based smart drying systems.

On the basis of the results obtained, it is possible to assert that an in-line CV system embedded into a hot-air-drying unit allows to precisely measure the area of shrinkage of apple slices, and then to predict changes in MC_{wb} of product through the linear relationship between the two parameters. No impact of the anti-browning treatment on the performance of the prediction models was noted. The practical implication of this study is that modelling the data acquired during drying through computer vision can provide useful information concerning the physicochemical changes of product. Thus, the proposed approach lays the foundations for a more efficient smart dryer that can be designed, and its process optimized for drying of apple slices, reducing the human error, production cycle time, analytical time and costs.

ACKNOWLEDGEMENTS

The authors gratefully acknowledge [1] CORE Organic Plus consortium (ERA-NET action) and MIPAAF (Ministero delle politiche agricole alimentari e forestali - Italy) for financial support through the SusOrgPlus project (D.M. 20/12/2017, n. 92350) and [2] the 'Departments of excellence 2018' program (i.e. 'Dipartimenti di eccellenza') of the Italian Ministry of Education, University and Research (MIUR) for the financial support through the 'Landscape 4.0 food, wellbeing and environment' (DIBAF department of University of Tuscia) Moreover, our sincere thanks to Gianpaolo Moscetti and Swathi Sirisha Nallan Chakravatula for the English language revision of the manuscript.

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