Computers and Electronics in Agriculture 138 (2017) 157–166

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Original papers

Characterizing apple microstructure via directional statistical correlation functions

A. Derossi [a,*], B. Nicolai [c,b], P. Verboven [b], C. Severini [a]

[a] Department of Science of Agriculture, Food and Environment, University of Foggia, Italy
[b] KU Leuven – University of Leuven, Division MeBioS – Postharvest Group, Willem de Croylaan 42, BE3001 Leuven, Belgium
[c] Flanders Centre of Postharvest Technology (VBCT), Willem de Croylaan 42, BE3001 Leuven, Belgium

ARTICLE INFO

Article history:
Received 15 January 2017
Received in revised form 31 March 2017
Accepted 25 April 2017

Keywords:
Statistical correlation functions
X-ray microtomography
Apple tissue
Modeling microstructure

ABSTRACT

Our understanding of food is tightly related to the complex food microstructure. We introduce the use of statistical correlation functions to quantitatively describe the spatial distribution of cell and void phases of 'Braeburn' and 'Kanzi' apples. The lineal-path distribution function, $L(r)$, and the two-point correlation function, $S_2(r)$, were measured from bi-dimensional (2D) microtomographic images. While the void fraction of both apples cultivars was similar, 0.840% and 0.853%, the pores of 'Braeburn' apples were bigger in size. Pores with an extension of 25 μm were found in percentage of 12.6% and 4.3% for 'Braeburn' and 'Kanzi' respectively. The cell phase of 'Braeburn' apples was described by larger clusters as a result of a greater degree of connectivity among the individual cells. 'Kanzi' apple tissue was structured by more separated cell clusters due to the presence of small pores with a greater spatial distribution. The clusters showed a good homogeneity in shape for both varieties while the voids of 'Kanzi' apples appeared more inhomogeneous and elongated in one of the dimensions. The obtained structural information were employed to model tissue structures of apples. We found that the cell phase could be modeled by overlapping disks having a mean radius of 58 and 53 mm for 'Braeburn' and 'Kanzi' apples, respectively. In this way macroscopic properties of apple tissue could be estimated precisely.

1. Introduction

Foods are microstructured and contain elements below the 100 μm range (Aguilera, 2005), which are connected with a high degree of disorder defining the three dimensional architecture of food. The single elements may be solids, liquids or gases. As a consequence, food may be considered as two-phase random media composed of a void phase (i.e., the pores) and a solid and/or liquid matrix phase (i.e., cells, cell walls, crystals, globules, oil droplets, etc.). The complex three-dimensional (3D) architecture of pores and matrix elements greatly affects physical, sensory and chemical properties of the food as well as microbial growth (Datta, 2007; Derossi et al., 2016). Examples of foods consisting of two-phase random systems are bread, biscuits, cake, cheese, ice-cream, roasted coffee beans, meat, fruit and vegetables, etc. Considering fresh fruit, the micro-architecture in the tissue significantly changes during ripening and storage. Han et al. (2006) observed the separation of cell walls of mango in the first stage of ripening followed by the swelling of the cell walls during the last stage of the process. Cantre et al. (2014) proved that by analyzing the 3D micro-architecture of mango it was possible to determine its quality during ripening stages. The importance of the 3D microstructure on the texture and mechanical attributes of fruit was described by Mebatsion et al. (2008). Moreover, microstructural properties of apple and pome fruit were used to model gas exchanges with the environment which affect the evolution of quality during postharvest storage (Verboven et al., 2008; Ho et al., 2011; Herremans et al., 2014). However, apart from the effect on fresh products, the understanding of microstructural changes during processing such as dehydration, freeze-drying, freezing, thawing, blanching, cooking, etc., would be of utmost importance for improving the quality of food products on the market as well as for optimizing food processing operations. Under these considerations, the definition of the essential morphological information to characterize food microstructure, its exact theoretical and experimental quantification are of crucial importance as well as the use of this information to estimate the macroscopic properties of food and their change during ripening, storage or processing.

Food microstructure is often quantified by a series of common measures (porosity fraction, void size, shape factor, void count, level of anisotropy, level of connectivity, etc.). Although these

* Corresponding author.
E-mail address: antonio.derossi@unifg.it (A. Derossi).

http://dx.doi.org/10.1016/j.compag.2017.04.021
0168-1699/

simple measures provide useful information, the enormous amount of data associated with the internal microstructure cannot be sufficiently described by them. In addition, as reported by Hiushkou et al. (2015) for the complex geometry of real materials, a precise prediction of properties such as diffusion, electrical or thermal conduction cannot be obtained by the common class of information such as porosity, connectivity, fractal dimension, etc., but higher degree statistical information is required. In the last 20 years, an alternative approach to study microstructure of materials based on statistical continuum theory is attracting the interest of investigators in many research fields. In this approach the macroscopic properties of materials are related to the local geometry described by a set of distributions with an increasing order of statistics. The most important quantities in this theory are the statistical correlation functions (SCF) which have been proved to be very useful to describe a wide spectrum of random complex systems (Lu and Torquato, 1992a, 1993; Coker and Torquato, 1995; Jiao et al., 2007). However, since the complete characterization of microstructure would need an infinite number of SCFs, only low order microstructural information may be practically obtained. One of the basic quantities is the *two-point correlation functions*, $S^i_2(r_1,r_2)$, which describes the probability to find two points, r_1 and r_2, in phase *i*. The *lineal-path distribution function*, $L^i(r)$, is the probability to find a segment of length *r* completely in phase *i* when it is randomly placed in the system. It was proven that this function contains important clustering information along a straight line (Lu and Torquato, 1992b; Rintoul et al., 1996). Other SCFs functions are the *chord-length distribution function*, $p(z)$, *pore size distribution function, P(z)*, *nearest-neighbor correlation function*, *pair correlation function*, *two-point cluster function*, $C^i_2(r)$, etc. (Torquato and Lu, 1993; Quintavalla and Torquato, 1996; Torquato, 2002; Jiao and Chawla, 2004). The above morphological quantities were extensively used to obtain a high degree of information of digitized model systems (Lu and Torquato, 1992a, 1992b; Jiao et al., 2007) and real materials such as Boron modified Ti-alloys (Singh et al., 2008), gels (Rintoul et al., 1996) and for the spatial organization of cell nuclei in brain tumors (Jiao et al., 2011). In addition, SCFs were used to estimate the water retention curve of soil (Chan and Govindaraju, 2004), effective diffusion coefficients in random systems (Hiushkou et al., 2015), transport properties in gels (Rintoul et al., 1996), etc. On the other hand, the application of SCFs to foods has been limited so far (Derossi et al., 2012, 2013, 2014, 2016). Derossi et al. (2012) used the lineal-path distribution function to obtain morphological information of fat and meat phases of fermented sausages. Later the same authors showed that the microstructure of bread may be modeled as a system of polydispersed overlapping disks (Derossi et al., 2013a, 2013b). However, based on our knowledge, statistical correlation functions were never used to describe fruit or vegetables microstructure. On these bases the main aim of this paper was to introduce the use of statistical continuum theories to obtain information on the microstructure of fruit and vegetables. More specifically, *the lineal-path distribution function*, *L(z)* and the *two-point correlation function* $S_2(r)$ were estimated from 2D X–ray tomographic images of 'Braeburn' and 'Kanzi' apples and compared for both cell and void phases. Also, we used some basic random theoretical systems to model the microstructure of apples tissue.

2. Materials and methods

2.1. Apple samples and image acquisition

Apple fruit of the cultivars 'Kanzi' and 'Braeburn' were harvested from orchards in Belgium at optimal picking dates in September and October 2014, respectively, and transported to KU Leuven in November 2014. Fruit was stored in controlled atmosphere conditions until the time of X-ray imaging in January 2015. Conditions were 1 °C, 2.5% O_2, <0.8% CO_2 for 'Braeburn' and 4 °C, 2% O_2, 0.8% CO_2 for 'Kanzi' according to the recommendations of the Flanders Centre of Postharvest Technology (www.vcbt.be).

X-ray tomography (micro-CT) was applied to visualize the porous microstructure of the apple cortex tissue samples according to the procedures of Herremans et al. (2015) using a Skyscan 1172 (Bruker microCT, Kontich, Belgium). This resulted in a stack of cross-sectional images of the cortex at 5 mm below the peel on the equator of the apples. The cross sectional slices perpendicular to the fruit radius consisted of 1600 $(x) \times 1600$ (y) pixels with a pixel size of 4.9 μm. A central region of interest of 600 × 600 pixels was used for further analysis. The grayscale images were segmented into cells and pores by using Otsu's method (Herremans et al., 2015). Representative grayscale and segmented image slices are shown in Fig. 1.

2.2. Theoretical background

Let us assume an apple tissue consisting of a void phase (i.e., the pores) and a cell phase, respectively having a void fraction, ϕ_1, and a solid fraction, ϕ_2. To characterize this system the introduction of an indicator function, $I^i(x)$ is of main importance:

$$I^{(i)}(x) = \begin{cases} 1, & \text{if } x \text{ falls in the phase } i(\varepsilon\Upsilon_i) \\ 0, & \text{otherwise,} \end{cases} \tag{1}$$

where Υ_i is the region occupied by phase *i* (equal to 1 or 2) (Lu and Torquato, 1992a). For clarity, in this paper we will refer to the void phase as phase 1 and cell phase as phase 2.

2.3. Lineal-path distribution function, L(r)

The lineal-path correlation function, $L^i(r)$, gives the probability that a randomly chosen segment of length *r* completely falls in the phase *i*. For *r* = 0, the lineal path function $L^i(0)$ is the probability to find a point in the phase *i*, that is the volume fraction of the phase *i*, ϕ_i. (Lu and Torquato, 1992a). The lineal path function contains important connectedness information along a lineal-path; nevertheless, it generally underestimates the clustering degree because it is unable to consider two points belonging to the same cluster but not along the same lineal-path. Moreover, it was proven that, for three dimensional systems, $L(r)$ is equivalent to the area fraction of phase *i* measured from the projected image of a three-dimensional slice of thickness *z* onto a plane. Furthermore it is also strictly related with another important morphological quantity, i.e. the chord-length distribution function (Lu and Torquato, 1993; Rintoul et al., 1996).

2.4. Two-point correlation function, $S_2(r)$

The two-point correlation function, $S_2^{(i)}(\mathbf{x}_1,\mathbf{x}_2)$, gives the probability that two arbitrarily selected points are in the phase *i*. This function may be defined as (Yeong and Torquato, 1998)

$$S_2^{(i)}(\mathbf{x}_1,\mathbf{x}_2) = \langle I^{(i)}(\mathbf{X}_1,)I^{(i)}(\mathbf{X}_2)\rangle \tag{2}$$

where angular brackets define an ensemble of average particles. For homogeneous systems the S_2 function only depends on the vector distance between the two points x_1 and x_2,

$$S_2^{(i)}(\mathbf{x}_1,\mathbf{x}_2) = S_2^{(i)}(\mathbf{x}_1-\mathbf{x}_2) = S_2^{(i)}, \tag{3}$$

where $r = |\mathbf{x}_1 - \mathbf{x}_2|$. At *r* = 0 the correlation functions gives the probability that a random selected point is in the phase *i*, i.e. the volume fraction of the phase of interest, ϕ_i . Also, a second important property of S_2 is that