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Postharvest noninvasive assessment of undesirable fibrous tissue in fresh processing carrots using computer tomography images

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ABSTRACT

This research was designed to develop and test an automatic image analysis method (algorithm) to classify CT images obtained from 1233 carrot (*Daucus carota* L.) sections (samples), collected during the 2013 and 2014 harvesting seasons. Classification accuracy was evaluated by comparing the classes obtained using eighteen CT images per carrot section to their undesirable fibrous tissue class, based on the industry-simulated invasive quality assessment (% of fiber). Class-0 represents fibrous-free samples, and class-1 denotes samples containing fibrous tissue.

After CT image preprocessing, cropping, and segmentation, 3762 grayscale intensity and textural features were extracted from the eighteen CT images per sample. A 4-fold cross-validation linear discriminant classifier with a performance accuracy of 87.9% was developed using 95 relevant features, which were selected using a sequential forward selection algorithm with the Fisher discriminant objective function. This objective method is accurate in determining the presence of undesirable fibrous tissue in pre-processed carrots.

1. Introduction

Carrot (*Daucus carota* L.) is an economically important produce grown around the world, including the United States (Sood et al., 1993; Nyman, 1994). In 2014, around 322 thousand tons were produced in the US for the processing/value-added market, yielding a total revenue of approximately 37.2 million US$ (USDA/NASS, 2014). In the value-added market, carrots are usually partly processed, which includes washed, peeled, sorted, sliced or diced (6.35 mm–12.7 mm cubes), and quick frozen so that no, or slight, additional preparation is required for final use (Rico et al., 2007; Hodges and Toivonen, 2008). Partially processed carrots are then integrated into a variety of products, including baby food, mixed vegetables, and dehydrated soups (Howard and Griffin, 1993; Burns, 1997).

Quality and safety of fresh and processed agro-food commodities, including carrots, are measured not only by external factors such as shape, foreign objects presence (Jha et al., 2010), color (Wu et al., 2014), size, surface blemishes (Jha and Matsuoka, 2002), and mold, but also by internal quality and safety features, which are essential for consumer acceptance (Kotwaliwale et al., 2014). Carrot internal features include the presence of undesirable fibrous tissue (Donis-González et al., 2015), tough-tissue (McGarry, 1995), moisture-content (Firtha, 2009), nutrient-content (carotenoids, ascorbic acid, and calcium) (Liu et al., 2014), and texture (Rastogi et al., 2008). Donis-González et al. (2015) expressed that fibrous carrots are undesirable and difficult to detect and eliminate. Fibrous carrot dices are especially problematic when found in ready-to-eat infant food, where they might represent a choking hazard (safety concern).

Currently, noninvasive systems mainly using inline color computer vision techniques are used to determine external quality attributes, such as color, external defects, and shape in fresh and processed vegetables, nuts, and fruits (Brosnan and Sun, 2004; Mery and Pedreschi, 2005; Blasco et al., 2007; Gomes and Leta, 2012; Moreda et al., 2012; Donis-González et al., 2013). In addition, techniques based on near-infrared (NIR), X-ray, computed tomography (CT), magnetic resonance imaging (MRI), vibration, sonic and ultrasonic, have also been applied for non-destructive determination of internal quality attributes of a variety of agricultural and food products (Milczarek et al., 2009; Cubero et al., 2010; Lorente et al., 2011).

Internal quality attributes, which have been explored in carrots,

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include: Texture and sweetness using visible and NIR reflectance measurements (Belie et al., 2003); nutritionally valuable compounds content (i.e. vitamin C, α-carotene, β-carotene, sucrose, glucose, and fructose) by applying spectrophotometric sensing (Zude et al., 2007); and moisture loss by NIR spectroscopy (Kaffka et al., 1990) as well as hyperspectral imaging (Firtha, 2009). In CT, the difference in physical density of materials, including those within fresh and processed agro-food commodities, is visualized by changes in image grayscale intensity and is expressed in 'Hounsfield-Units' (HU) (or 'CT-number') (Bushberg et al., 2002; Donis-González et al., 2012a; Donis-Gonzalez et al., 2012b). Despite widespread research efforts and off-line application studies, involving those of carrots, an automatic real-time inline CT inspection system for the classification of processing carrots and others commodities is not commercially available. Because of recent advances in high-performance computing systems, non-medical CT applications are gaining attraction. Latest advances include modern graphical processing unit (GPU) computing capabilities (Pratx and Xing, 2011), high-performance X-ray tubes, new concepts for high-throughput inline CT inspection systems and new detector technologies offering real-time imaging including electron beam CT, equipment cost decreases, extended or continuous operation equipment, and significant reduction in image reconstruction time (Hampel et al., 2005; Hanke et al., 2008; Bierberle et al., 2009; Stuke and Brunke, 2010; Donis-González et al., 2014b). With the aim of studying pre-harvest carrot growth and the effect of fibrous tissue in fresh carrots, Rosenfeld et al. (2002) evaluated the pre-harvest growth and development of carrot roots by means of X-ray CT, with minimal disturbance to potted carrot plants. Also, Donis-González et al. (2015) used CT technology to visualize the presence and study the effect of undesirable fibrous tissue in processing carrots, as well as studying related changes in carrot structural fiber polymers. Images, better understanding of the presence and impact of undesirable fibrous tissue can be seen in Donis-González et al. (2015). Previously, using a CT system as a tool, Donis-González et al. (2012a; 2012b) found a significant relationship between CT images and chestnut (*Castanea* spp.) internal components. Furthermore, an automatic, accurate, reliable, and objective tool to determine chestnut internal quality (decayed tissue) using CT images, applicable to an automated noninvasive inline CT sorting system, was developed by Donis-González et al. (2014a). However, currently only destructive techniques, off-line monitoring, or random sampling can be reliably employed at the processing plants with the objective of evaluating the presence of undesirable fibrous tissue in carrots. Clearly, invasive techniques can't be applied to all produce and, thus, it is crucial to develop an *in vivo* inline nondestructive tool capable of better detecting carrots containing undesirable fibrous tissue. This will enable the carrot processing industry to offer a better quality and safer product, therefore increasing consumer satisfaction and decreasing industry liability issues.

If CT inline systems were to be developed, little is currently known about how to efficiently handle and analyze the high amount of acquired data, while continuously scanning. Pattern recognition algorithms, which are an important and intrinsic part of computer vision systems (Duda et al., 2000; Mery and Soto, 2008), offer a mechanism of classifying commodities based on their quality attributes, and can be applied to CT systems, as seen in Donis-González et al. (2014a). Comprehensive information concerning statistical pattern recognition techniques can be found in multiple manuscripts, including Jain et al. (2000), Duda et al. (2000), Bishop (2007), and Holmström and Koistinen (2010).

Therefore, the objective of this study was to describe the methodology for developing an automated classification algorithm to detect the presences of undesirable fibrous tissue in CT images of processing carrots, which would be suitable for an inline CT inspection system.

2. Materials and methods

2.1. Carrot collection and preparation

Steps used to generate the pattern classification algorithm to categorize internal carrot quality, based on their presence of undesirable fibrous tissue using CT images are illustrated in Fig. 1. A total of 411 fresh carrots (cv. 'Canada', a common and highly utilized cultivar for processing), equal or larger than 180 mm length (collar to tip), were directly hand harvested from six Michigan commercial production fields (Oceana county, MI) mid-November 2013 and 2014. Of the carrots, 219 were bolted (premature production of a seed-head) suspected of containing undesirable fibrous tissue, and 192 were non-bolted, likely fibrous-free. Carrots were randomized, numbered and manually cleaned with water, with the objective of removing excess dirt. Immediately after cleaning, samples were stored at 4 °C. Six days later, CT scans were conducted (Fig. 2).

2.2. In vivo CT imaging scans

CT scans were performed using a GE BrightSpeed®[1] RT 16 Elite, multi-detector CT instrument (General Electric Healthcare, Buckinghamshire, United Kingdom) on a polyethylene board (915 mm × 335 mm × 2.8 mm) placed on the CT scanner table, containing a maximum of 12 carrots, as seen in Fig. 2a. Scanning procedure and image output is as described in Donis-González et al. (2014a). Scanning parameters, which were optimized using the procedure described in Donis-González et al. (2012a), are summarized in Table 1.

A single scanning of the CT system consists of a block of 3D data stored as voxels. Voxels (volume elements), have the same in-plane dimensions as pixels (2D image elements), but also include the slice thickness (*d*) dimension (Bushberg et al., 2002). However, the entire block of data is not acquired at once. Instead, each XY plane 2D CT image slice (XY-plane-slice) is processed as the carrots, previously arranged in rows and placed on the scanning board, are passing though the CT scanner. A XY-plane-slice is analogous to a virtual cross-section of the imaged carrot passing through the CT scanner. Therefore, the imaging procedure is done one XY-plane-slice (cross-section) at a time, starting with t_1-and ending with t_n-XY-plane-slice. The originally acquired CT XY-plane-slices, containing images from several carrots per row, moving through the Z-axis (longitudinal direction), are stored in memory using a digital imaging and communications in medicine (DICOM) standard format, as observed in Fig. 2b. In the case of CT, the difference in physical density of materials is visualized by changes in grayscale image intensity of the DICOM image.

2.3. CT image preprocessing

Image preprocessing (re-slicing, cropping and contrast enhancement), image visualization, segmentation, feature extraction, statistical analysis, and the automatic classification/validation for this study were done in MATLAB (2012a, The MathWorks, Natrick, MA, USA) (http://www.mathworks.com), and in the language and environment for statistical computing software R (V2.10.0, R Development Core Team, Vienna, Austria) (http://cran.r-project.org/), using a Macintosh environment on a Lion operating

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