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5 **Postharvest noninvasive assessment of undesirable fibrous**
6 **tissue in fresh processing carrots using computer tomography**
7 **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.

Keywords: Quality; safety; classification; computer vision; X-ray

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 to 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., 2011). 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, 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 x 335 mm x 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 through 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

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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, Natick, 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 system with 2.53 GHz Intel Core 2-Duo, 8 GB random access memory (RAM), 1067 MHz double data rate 3 (DDR3) (Apple Inc., Cupertino, California, USA). Feature extraction, feature reduction, and the automatic classification/validation for this study were performed using the “Balu” free MATLAB toolbox for pattern recognition (<http://dmery.ing.puc.cl/index.php/balu/>), developed by the Department of Computer Science at the Pontifical Catholic University of Chile (Santiago, Chile). This toolbox contains functions for image processing, feature extraction, feature transformation, feature analysis, feature selection, classification, clustering, performance evaluation, image sequence processing, and more.

16-bit grayscale carrot DICOM images (<http://medical.nema.org/>) were imported into MATLAB and mapped to the original HU-values.

2.3.1. CT image re-slicing

Depending on carrot physical size and d , each carrot contains between 72 to 125 XY-plane-slices representing virtual cross-sections of a carrot along the longitudinal (Z) axis

(from collar to tap root). Using a process known as re-slicing, as visualized in Fig. 3 (Bushberg et al., 2002) originally acquired XY-plane-slices from one or several carrots (e.g. Figs. 1, 2b, 3c, 4c, 4e) can be reconditioned into two different planes, results in a series of YZ-plane-slices (e.g. Figs. 3b, 4d, and 4g), and XZ-plane-slices (e.g. Figs. 3d, 4a, 4b, and 4f). As before, depending on carrot size and d , each carrot contains 65 to 100 YZ-plane-slices and XZ-plane-slices.

2.3.2. Individual carrot CT image cropping

Carrot rows and individual carrots were manually/visually cropped from the overall CT data set containing the scanning table, volume of air and other carrots, by determining their spatial location, as shown in Fig. 4. In Fig. 4a, Z_1 - and Z_2 -spatial-location-values are manually determined to crop each carrot row, generating Fig. 4b (row XZ-plane-slice), 4c (row XY-plane-slice) and 4d (row YZ-plane-slice). To crop an individual carrot, which in Fig. 4 has been surrounded by a red rectangle, X_1 -, X_2 -, Y_1 -, and Y_2 -spatial-location-values are manually inferred, as seen in Figs. 4a, 4b, 4c and 4d. Pixels in Figs. 4a through 4d correspond to the mean of all pixel values at the same planer location (xy , yz , xz), within each plane in each individual carrot image stack. Manual cropping guarantees that the pattern recognition algorithm is not affected by cropping errors, and was only done for the purpose of this study. An automatic cropping/recognition algorithm should be applied, if an inline system is used. Automatic cropping can efficiently be done through a heuristic approach, or by applying simple intensity operations, which are not computationally time intense and insignificant in comparison to the time it takes to acquire and classify CT images.

For each carrot that is re-sliced making up the three different planes, a data set of up to approximately 375 *raw* CT image slices of about 75 x 75 pixels each (depending on the carrot physical size) are generated. For further analysis, data set dimensionality is then reduced from these original *raw* CT images per carrot sample to 6 resultant CT images per sample (A). Three mean and three maximum intensity value CT images from the three different planes (XY, XZ and YZ) are obtained per carrot (total of 6), as exemplified for the mean intensity value CT images in Figs. 4e-4g. Mean and maximum intensity images were used for internal quality classification, because it has been previously determined that these images directly and visually relate to fresh carrot internal characteristics, as seen in Donis-González (2015).

2.3.3. Contrast enhancement and image noise reduction

Contrast enhancement and image noise reduction were vital steps in image processing, which are done to increase image quality (Wang et al., 1983; Zimmerman et al., 1998; Jagannath et al., 2012). Multiple techniques exist, which are used to improve digital image contrast and reduce image noise, including morphological operations enhancement and filtering as described in Sreedhar and Panlal (2012).

In this study, based on the knowledge obtained from Donis-González (2012a; 2012; 2014a; 2015), one contrast-enhancement-technique and one image-noise-reduction-technique were implemented, to increase original (A) CT image contrast and reduce noise, before classification. These techniques were applied to the 6 resultant CT-images per carrot (Section 2.3.2) denoted as A, following the procedure in Wirth et al. (2004) and Sreedhar and Panlal (2012).

For each carrot segment, a set of contrast-enhanced-CT-images (set_*B*) are generated from the set of 6 resultant CT-images (set_*A*), by first generating adjusted mean and maximum CT images. This first step is done by mapping the outputted CT image grayscale values from their corresponding image *A*, so that 1% of their pixels at low and high intensities (2% in total) are saturated (limited to lowest and maximum pixel values). Second, a top-hat operation (high grayscale intensity regions) using a 5 neighbors disk shaped flat structuring elements (SE) is applied to the adjusted CT image, generating the top-hat image. Third, a bottom-hat operation (low grayscale intensity areas) using the same SE as described in previous step is also applied to the CT adjusted image, creating the bottom-hat image. The form and size of the SE is appropriate because of the shape of the carrots, reflected in the CT images. Finally, set of 6 resultant contrast-enhanced-CT-images (set_*B*) are produced by adding the top-hat image to its corresponding adjusted image and subtracting its linked bottom-hat image (i.e. adjusted image + top-hat image – bottom-hat image). This stretches the high intensity areas toward increased intensity, while low intensity regions are stretched towards decreased intensity.

A set of 6 resultant noise-reduced-CT-image (set_*C*) was generated for each of the 6 contrast-enhanced-CT-images (set_*B*), by applying a two dimensional median filtering methodology to the previously generated contrast-enhanced-images (set_*B*). Each output pixel contains the median value in the 3-by-3 neighborhoods around the corresponding pixel in the corresponding contrast-enhanced-image (*B*). Median filtering is a nonlinear operation regularly used in image processing to reduce noise (Sreedhar and Panlal, 2012). Therefore, 18 resultant CT images per segment (3-image types: *A*, *B*, and *C* reconditioned onto 3-planes: XY, YZ, and XZ; from maximum, and minimum CT images) were

obtained and used for classification, as depicted from Fig. 1. To better understand contrast enhancement and noise reduction steps, the reader is referred to Nixon and Aguado (2008).

2.4. Manual/destructive quantification of carrot fibrous tissue and sample preparation

Immediately after CT scanning, manual/destructive quantification of undesirable fibrous tissue was completed. For the purpose of this study, individual carrots were divided into three segments/sections (57 mm length), each representing a different sample (Fig. 1, symbolized in red – S1, S2, and S3). This was acceptable, as carrots are large (> 180 mm), and location of each segment is easily and automatically inferred in the CT image stack. Thus, from the 411 collected carrots, 1233 carrot samples (fragment segments) were extracted/cut, using a sharp hand knife, starting 10 mm into carrot collar (top). Color images of the freshly cut top-end of each segment (sample) were acquired using an 8-megapixel, *f*/2.4 aperture Iphone 4s camera (Apple Inc., Cupertino, CA, USA) for record keeping and to use as a visual reference. Examples of color images can be seen in Figs. 1 and 5. Thereafter, with the objective of quantifying carrot fibrous tissue, and approximating the location of the presence of fibrous tissue in each carrot, samples (segments) were processed mimicking the dicing processing industry.

First, samples were manually peeled, and longitudinally cut into 6.35 mm width cuboids, using a manual French fry cutter/slicer (New Star Foodservice Inc., Chino, Ca, USA). Second, each cubed sample was identified, weighed (total segment weight) and put into a mesh-bag. Third, mesh-bags containing cuboids were cooked at approximately 90 °C for 1 h in industrial steam heated kettles (Model D10SP, Groen, Chicago, Il, USA). Fourth, each set of carrot segment cuboids was individually and manually strained using a

4.5 mm diameter-hole manual ricer (Browne FoodServices, Ontario, Canada). Fifth, carrot tissue that did not pass through the manual ricer was manually filtered over a 2 mm stainless steel sieve, using sprayed water, until all soft fibrous-free carrot tissue passed through the sieve. Sixth, remaining tissue, if any, was collected and weighted. Thereafter, carrot segments were qualified into two classes, as either containing undesirable fibrous tissue (class-1) or not (fibrous-free, class-0). More information regarding carrot CT image visualization in relation to their fresh state can be seen in Donis-González et al. (2015).

2.5. CT image segmentation (Binary mask) from different carrot components (1-whole carrot, 2-xylem, 3-vascular cambium, and 4-phloem):

Image segmentation is used to recognize the region-of-interest (ROI) in an image from each sample. Based on Donis-González et al. (2015), where it was determined that distinctive carrot components are differently affected by the presence of undesirable fibrous tissue in fresh processing carrots, four different ROI sets were generated for this study. ROIs were designed to separately involve the following carrot internal tissue components: 1-whole carrot, 2-xylem, 3-vascular cambium, and 4-phloem.

Whole carrot (1-Binary mask) segmentation was done by using the balanced histogram thresholding method, as described in Anjos and Shahbazkia (2008). This is a broadly used histogram based thresholding procedure. This methodology assumes that the CT image is divided in two classes, (1) the foreground (carrot CT image, pixels = 1 – white) and (2) the background (air, pixels = 0 – black). To do so, the methodology finds the optimum threshold level (first minimum grayscale value in the mean CT image histogram) from the resultant CT mean slice, dividing the image into the two classes. Thereafter, based on carrot morphology, image morphological operations (eroding and dilating) were

empirically applied to recognize the additional ROIs (2-xylem, 3-vascular cambium, and 4-phloem). Description and understanding of morphological operations can be found in Nixon and Aguado (2008), and in Gonzalez et al. (2009). Using an erosion operation onto the whole carrot segmented image (1-Binary mask) generated the segmented xylem image (2-Binary mask). Using a flat disk SE equal to the whole carrot major axis length divided by its minor axis length performed this erosion. Vascular cambium segmented image (3-Binary mask) was created by applying a dilation operation to the perimeter of the segmented xylem (2-Binary mask). This dilation was done by using a flat disk SE equal to 8 (constant), and a pixel is part of the xylem (2-Binary mask) perimeter if it is equal to 1 and it is connected to at least one zero-valued pixel (Gonzalez et al., 2009). Phloem segmented image (4-Binary mask) was produced by subtracting a sub-set dilated xylem image from the whole carrot segmented image (1-Binary mask). In the latest, sub-set xylem dilation was completed by using a flat disk SE equal to 1 (constant).

The segmentation procedure was visually validated and it is robust, dependent of carrot size, shape and morphology, but independent of the amount of undesirable fibrous tissue in each carrot. Example of segmented ROIs in whole carrots can be found in Fig. 1, where segmented ROIs or binary masks, for each component, can be seen in green superimposed regions (pixels = 1) on mean CT images from the three different planes (XY, YZ, and XZ).

2.6. Feature extraction:

In this study, features were extracted from the eighteen 16-bit CT resultant intensity image sets (A, B, and C) per ROI (whole, xylem, vascular cambium, and phloem) in each carrot sample, as previously described in Sections 2.3, and 2.5. A total of 209 features

were extracted per CT image, and then features from the eighteen CT images were concatenated to form a feature vector (x) per ROI. Each x contained 3762 components, as partially illustrated in Fig. 1. Extracted features per CT image and ROI included: (1) 6 basic intensity features (Shapiro and Stockman, 2001; Nixon and Aguado, 2008; Mery et al., 2011), (2) 26 Haralick textural (T_x) features (Haralick, 1979; Mery et al., 2010; Donis-González et al., 2013), (3) 95 intensity local binary pattern (LBP) features (Pietikäinen et al., 2000; Ojala et al., 2002a; Ahonen et al., 2009; Chai et al., 2013), (4) 67 Gabor intensity textural features (Kumar and Pang, 2002; Zhang, 2002; Ng et al., 2005; Zhu et al., 2007; Mery and Soto, 2008), (5) 5 contrast features (Kamm, 1998; Mery, 2001; Mery and Filbert, 2002), and (6) 10 texture features based on local Fourier transform (FFT) (Feng et al., 2001). Some of the extracted features are exemplified in Fig. 5.

2.7. Feature selection:

After feature extraction, it is necessary to select the best features for each ROI separately to train each classifier (Mery and Soto, 2008). The purpose of the feature selection step, also known as feature reduction, is to obtain a smaller subset of features (m) from the original data set (x), which will yield the highest classification rate possible (Jain et al., 2000). High dimensionality increases time and space requirements for processing data. Also, in the presence of irrelevant and/or redundant features, classification methods tend to over-fit and become less interpretable, especially when the number of features is much larger than the number of samples. Feature selection algorithms usually involve maximizing or minimizing an objective function (f), whose output can be calculated for the generated m , therefore measuring their classification potential (effectiveness) and working as a feedback signal to select the best features.

In this study, the sequential forward selection (SFS) technique (algorithm), taking feature dependencies into account (eliminates features that are highly correlated $r \geq |0.95|$) (Silva et al., 2002), was selected as a search strategy (Jain et al., 2000). No more features are added, when no significant classification performance is observed ($< 0.5\%$). Three different objective functions were evaluated in this study: (1) the Fisher score ($J(W)$) (Duda et al., 2000), (2) linear discriminant analysis (LDA) (Duda et al., 2000; Quanquan et al., 2011), and (3) quadratic discriminant analysis (QDA) objective functions (Jain et al., 2000; Bishop, 2007).

2.8. Classification (training and validation):

A supervised learning approach was used to separately develop a different classifier based on each of the ROIs (Duda et al., 2000). Supervised classes, known as labels, were based on 2-categorical-group, where each sample was invasively categorized into 2-classes, based on their content of undesirable fibrous tissue. Samples either contain undesirable fibrous tissue (class-1) or not (fibrous-free, class-0). Optimum uniform sample distribution, used to train and validate the 2-class-classifier, can be observed in Fig. 6a. In addition, Fig. 6b includes a percentage (%) of fiber distribution and box-plot for the carrot samples containing undesirable fibrous tissue (class-1). Fig. 6b shows a positive skewed percentage (%) of fiber distribution, meaning that the class-1 group presents a higher frequency of low fibrous tissue content ($< 15\%$) samples. This positive-skewed fiber content distribution is beneficial for the robustness of the classification algorithm, as it is known that low fibrous content samples are naturally more prevalent and tougher to detect (Personal communication with Bakker, 2012).

Using the optimized selected features obtained from section 2.7, decision boundary lines, planes, and hyper-planes were implemented using LDA (Section 2.7), QDA (Section 2.7), Mahalanobis distance (MD) (Duda et al., 2000), a two-layer artificial neural network (ANN), a three-layer ANN using a logistic activation function, and a three-linear ANN using a Softmax activation function following the applied procedure in Ren et al. (2006; 2010), Mery et al. (2010), Leiva et al. (2011), and Donis-González et al. (2013). In general, this step assigns the object (i.e. set of 18 resultant CT images per sample) to a specific category (class).

Performance of each of the classifiers was measured as the correctly classified samples, using the set of 18 CT images per ROI, in reference to its supervised categorical class (label). Classifier validation was implemented using a 4-fold stratified cross-validation technique, therefore yielding an average estimate of classifier performance with 95% CI (Confidence Intervals) for the classification pool (Jain et al., 2000). Cross-validation was repeated four times, using 75% of the samples for training and 25% for validation.

3. Results

In this study, extracted features (x) were reduced from 3762 to 95 selected features (m – 2-class classifier), in order to avoid overtraining. Feature reduction was implemented using different algorithms. The SFS with the Fisher discriminant objective function ($J(W)$) method yielded the best overall features, resulting in the best classifier performance. The other feature selection methods, using additional objective functions, as described in Section 2.7 performed poorly (Results not included).

Results indicated that the best overall classifier is the LDA classifier, using vascular cambium segmented CT images as the ROI (3-Binary mask). Selected features (m) for the best classifier are noted in Table 2. Examples of image transformation (LBP, Gabor filters, and FFT) and other selected features (Tx , contrast & intensity), obtained from a fibrous-free (class-0) carrot sample and a sample containing undesirable fibrous tissue (class-1) can be seen in Figs. 5a and 5b, respectively. Other classifiers, using the different ROIs (whole, phloem and xylem) were also tested, however the overall classification performance was lower in all cases, as can be observed in Table 3. Performance results using the selected classifier, for increasing number of selected features (m), are included in Fig. 6c. Performance increases in relation to an increase in m and with 95 selected features (m) the classifiers had a high overall mean performance accuracy classification rate equal to 87.9%. Classifier performance slightly increased beyond the reduced number of selected features (m), but not notably ($< 0.5\%$), so additional features are not required to classify internal carrot undesirable fibrous tissue presence. In addition, it is not recommended to use a higher number of features to avoid classifier over-training, due to overall sample size, as recommended by Duda et al. (2000). Following the best classifier (ROI = vascular cambium), the classification rate of the different ROIs varied. Phloem, whole and xylem classification rate is equal to 79.2%, 77.6% and 75.7%, subsequently. In general, as it can be seen in Table 3, the overall best classifier in all the ROIs corresponded to the LDA classifier, in comparison to additional evaluated classifiers.

Fig. 6d includes the confusion matrix corresponding to the overall LDA classifier performance using vascular cambium segmented images. Each column of the matrix represents the occasions in a predicted class, while each row represents the instances in an

actual class. This matrix is beneficial, because it visibly documents the misclassified classes (Shapiro and Stockman, 2001).

4. Discussion

Textural features (98.9%) acquired from the different CT images are the most important features for classification, which include: (1) LBP features – 77.9%, (2) Gabor features at different scale and orientation – 8.4%, (3) FFT – 5.2%, (4) T_x and contrast features – 7.4%. Less influential, about 1.1% of the utmost important features involve the basic intensity features. Of the selected features (m), 59% have been extracted from originally acquired CT-images (A), 17% from contrast-enhanced-CT-images (B), and 24% from contrast-enhanced plus noised-reduced-CT-images (C), as seen in Table 2. Two examples of some of the transformations applied to a mean XY-plane-slice (A) CT images and extracted features can be seen in Fig. 5.

Textural features are essential because results cannot be credited to a single pixel value, but rather to numerous pixels in the image and their interaction. It can be inferred that LBP textural features are the most important features, because they captured the local structure and textural variations between carrot CT images, which contain undesirable fibrous tissue and carrots that are fibrous-free (Ojala et al., 2002b). LBP grayscale textural features. This can be visualized in the CT images and their corresponding LBP images in Fig. 5. Gabor textural features captured distinctive CT image information by means of merging different scaling and orientation elements. Gabor features, extracted from magnitude Gabor filtered images ($I_{rs}(i,j)$), have been found to be suitable for texture representation and discrimination (Zhu et al., 2007), thus it is hypothesized that Gabor features offer information regarding the development and presence of undesirable fibrous

tissue. Examples, of three magnitude Gabor images ($I_{rs}(i,j)$) generated by applying three
 different Gabor filters to mean CT images (XY-plane-slices) of a fibrous-free and a carrot
 sample containing fibrous tissue, can be found in Figs. 5a and 5b, respectively. These
 $I_{rs}(i,j)$ images are useful to visualize how Gabor features can differentiate between a carrot
 that contains undesirable fibrous tissue in comparison to a fibrous-free carrot. It is clear
 that Gabor filtered CT images of a carrot containing fibrous tissue present a higher level of
 textural elements in comparison with a fibrous-free carrot. As with Gabor features, inverse
 FFT images also indicate that CT images of a carrot containing fibrous tissue present a
 higher variability in textural attributes when comparing it to a fibrous-free carrot. This
 finding is consistent with other studies, where FFT features are utilized to describe texture
 similarities and grayscale pixel spatial dependences (Feng et al., 2001). In general, T_x and
 contrast features, which were also important, described the pixel spatial variation and their
 relationship in the segmented image. For example, CT images that contain pixels which
 are similar between each other have a lower value range ($T_{x(5,1)}$) in comparison to images
 containing a high variability of pixel intensity values, which have a higher contrast (K)
 and higher pixel value range ($T_{x(5,1)}$) (Haralick, 1979). Therefore, in this study, a **uniform**
 fibrous-free carrot that contains pixels, which are similar to each other will yield a low
 range - $T_{x(5,1)}$, and a low overall image contrast (K), as observed in Fig. 5a. On the other
 hand, CT images of carrots that contain undesirable fibrous tissue, having a high variation
 between pixels (e.g. undesirable fibrous tissue embedded in fibrous-free carrot tissue), will

present a higher pixel range ($Tx_{(5,p)}$) and a contrast values (K), as exemplified and specified in Fig. 5b.

While simple image intensity features only account for roughly 1.1% of the most important features, these features somehow summarize the overall quality appearance of the carrots in the CT images. For example, it could be quantified that carrots, which contain undesirable fibrous tissue, have a slightly lower intensity in comparison with healthy tissue (See Fig. 5). However, possibly because of the high variation between the CT images of the same class and CT image noise, simple intensity features by themselves do not provide enough information and are not as sensitive to accurately classify carrots, as it was initially hypothesized and briefly discussed in Donis-González et al. (2015).

After feature selection, 62% of the features were extracted from maximum intensity CT images, while only 38% are extracted from mean intensity CT images. It is hypothesized that this might be the case, because maximum images are less variable, have a higher contrast and can easily discern between fibrous and fibrous-free tissue. In addition, XY-plane-slices offer a higher amount of important features (68%) in comparison to reconditioned XZ-plane-slices (23%) and YZ-plane-slices (9%), which is similar with the findings in Donis-González et al. (2014a). The probable reason behind this is that image resolution (pixels mm^{-1}) is higher in the XY-plane in comparison to the images in the YZ- and XZ-planes (anisotropic voxels), as can be deducted from Table 1. Changes in image resolution comes from the fact that images are re-sliced onto the Z-axis using CT images that have been acquired every 2.5 mm (d), while pixel size in both the X and Y planes is equal to 0.976 mm, substantially smaller than d . It is hypothesized that this loss in resolution could be adjusted by assessing different CT image scanning techniques

and reconstruction algorithms, but future research is required to accurately address this topic. Also, the physiological development of undesirable fibrous tissue is consistent (surrounding the vascular cambium) and evident in the XY-plane-slice.

By analyzing the confusion matrix in Fig. 6d, it could be seen that classification error occurs slightly unevenly. In general, fibrous-free carrot samples (class-0) present a higher probability to be mistakenly classified as samples that contain fibrous-tissue (class-1). This is beneficial, as the processing carrot industry has expressed that discarded carrots are still useful as a by-product, but the presence of undesirable fibrous tissue in finalized processed products is unfavorable. In other words, it is preferred to discard carrots that are fibrous-free, in order for carrots containing fibrous tissue to be significantly reduced during processing (Personal communication with Bakker, 2012).

In general, results from this study show that CT images, acquired using a medical grade CT scanner, can be used as a technique that is able to classify carrots based on their undesirable fibrous-tissue content, regardless of the differences in carrot shape and analyzed carrot segment. **A unique finding of this study is that carrot shape did not paly a pivotal role in classification, as segmentation and feature extraction of the vascular cambium was independent of carrot morphology.** Carrots that do not contain fibrous tissue can be accurately separated from those containing undesirable fibrous-tissue with an 87.9% accuracy rate (2-class-classifier). This high classification rate can be accomplished with a relatively low number of features, with appropriate feature selection (*i.e.* = SFS), and classification techniques (*i.e.* = LDA). Feature reduction is imperative as it decreases computational time, hence allowing for possible in-line implementation. This study offers a procedure that can be followed to objectively forecast the overall quality of fresh

processing carrots. Even though the classification algorithm was developed using an off-line CT system, it assists the research community to better understand which features play an important role in the optimum classification of CT images. In addition, it offers a structure (procedure) that could be followed to create an inline noninvasive quality sorter of fresh processing carrots, and potentially other products. Transferring this tool to different commodity industries will allow them to build classification algorithms that could control and promote the quality and safety of their products.

In-depth discussion of cost, cost effectiveness, classification speed and potential applications of CT sorting systems in the agriculture and food industries can be found in Donis-González et al. (2014a; 2014b). In this study, image acquisition and reconstruction is equal to approximately 1.5 s per carrot. Feature extraction, re-slicing and classification together total 2.58 s per carrot. **This results in a classification throughput rate of approximately 1 carrot every 4 s, resulting in equipment that could sort between 8,640 to 17,280 kg of processing carrots on an 8 h shift day, without taking the manual cropping of images into consideration.** Future research, including optimized cropping procedures, equipment parameters and hardware modifications for inline sorting purposes, can significantly increase this throughput.

5. Conclusions

The CT imaging system provides high-resolution and high-contrast images of the internal structure and components of fresh processing carrots. Ninety-five selected features (m) were found to be effective in designing a LDA classifier with a 4-fold cross-validated overall performance accuracy of 87.9%.

Although the specific developed classification procedure (algorithm) is not directly applicable to other foods, agricultural commodities, or other applications, the methodology is valid for such. Before applying the classification procedure to other produce it will be necessary to train it appropriately. Findings showed that this methodology is an objective, accurate, and reliable tool to determine carrot internal quality, and would be applicable to an automated noninvasive inline CT sorting system.

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566 **Tables**

List of abbreviations	
<i>2D</i>	Two-dimensional image.
<i>3D</i>	Three-dimensional image.
<i>ANN</i>	Artificial Neural Network.
<i>CPU</i>	Central Processing Unit.
<i>CT</i>	Computed Tomography.
<i>DICOM</i>	Digital Imaging and Communications in Medicine.
<i>DDR3</i>	Double Data Rate 3.
<i>FFT</i>	Fourier transform, Fourier transformation.
<i>GPU</i>	Graphical Processing Unit.
<i>HU</i>	Hounsfield Units.
<i>kV</i>	Kilovolt.
LBP(d,h)	Local binary patterns.
LDA	Linear discriminant analysis.
MD	Mahalanobis distance.
<i>mA</i>	Milliamperage.
<i>MRI</i>	Magnetic Resonance Images.
QDA	Quadratic discriminant analysis.
<i>RAM</i>	Random Access Memory.
SFS	Sequential forward selection.
<i>Tx(k,p)</i>	Haralick Texture features.

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574 Table 1. Scanning parameters for the CT – General Electric, BrightSpeed™ RT 16 Elite
 575 (GE Healthcare, Buckinghamshire, England, Great Britain)

Units	Parameter
Voltage (kV)	120
Current (mA)	250
Slice thickness (pixel size in the Z-axis) (mm) – d	2.5
Pixel size (mm) in the X- and Y-axes	0.976
Pixel area in the XY-plane (mm ²)	0.952
Pixel area in the XZ- and YZ-planes (mm ²)	2.44
Voxel volume (mm ³)	2.381
Width of field of view (FOV) (mm)	500
Reconstruction matrix	512 x 512
Pitch (table movement – mm: rotation)	1.75:1
Time per rotation (s)	0.8
Scan time (s) per 1000 mm of board-length	18.1
Original image grayscale intensity resolution	16-bit
Total 2D CT images per 1000 mm of board-length (t_n)	400

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Table 2. Classifier selected features (m) from segmented vascular cambium (ROI) for the linear discriminant analysis (LDA) classifier using sequential forward selection (SFS) in combination with the Fisher discriminant objective function ($J(W)$)

n	Selected feature (m)	n	Selected feature (m)	n	Selected feature (m)
1	$\tilde{w}(5,3)$ [XY-max_B]	33	sLBP(1,36) [YZ-max_A]	65	FFT(1,2)-Ang [XY-max_C]
2	cLBP(1,6) [XY-max_A]	34	cLBP(1,3) [XY-max_A]	66	sLBP(1,54) [XZ-max_A]
3	Contrast-K [XY-max_A]	35	cLBP(1,23) [XY-mean_C]	67	cLBP(1,15) [YZ-max_A]
4	sLBP(1,10) [XY-max_C]	36	sLBP(1,17) [XZ-max_A]	68	$\tilde{w}(5,3)$ [XY-mean_A]
5	Tx(5,1)-Range [XY-mean_B]	37	sLBP(1,22) [XY-max_A]	69	$\tilde{w}(5,4)$ [XY-mean_A]
6	sLBP(1,47) [XY-max_C]	38	cLBP(1,19) [XY-mean_B]	70	cLBP(1,28) [XY-mean_B]
7	cLBP(1,9) [XY-max_C]	39	sLBP(1,12) [XZ-max_A]	71	sLBP(1,15) [XY-mean_A]
8	sLBP(1,36) [XY-max_C]	40	sLBP(1,46) [XY-mean_A]	72	sLBP(1,6) [XY-mean_C]
9	sLBP(1,19) [XY-mean_B]	41	cLBP(1,21) [XZ-max_A]	73	sLBP(1,17) [YZ-max_A]
10	Tx(14,1)-Range [XY-max_B]	42	$\tilde{w}(4,6)$ [XY-mean_A]	74	cLBP(1,7) [XY-mean_C]
11	sLBP(1,7) [XZ-max_A]	43	cLBP(1,6) [XY-mean_C]	75	cLBP(1,18) [XZ-max_A]
12	$\tilde{w}(1,1)$ [XZ-max_A]	44	sLBP(1,5) [XY-mean_A]	76	sLBP(1,56) [XZ-max_A]
13	sLBP(1,36) [XZ-max_A]	45	sLBP(1,40) [XY-mean_A]	77	Inten. skew. [XY-mean_A]
14	cLBP(1,3) [XZ-max_A]	46	cLBP(1,38) [XY-max_A]	78	Tx(14,1)-Range [XY-mean_B]
15	sLBP(1,38) [YZ-max_A]	47	sLBP(1,25) [XY-max_A]	79	Contrast-Ks [XZ-max_A]
16	sLBP(1,34) [XY-max_A]	48	sLBP(1,32) [YZ-max_A]	80	$\tilde{w}(1,1)$ [XZ-max_A]
17	sLBP(1,26) [XY-mean_B]	49	cLBP(1,12) [YZ-max_A]	81	sLBP(1,15) [XY-mean_C]
18	FFT(2,2)-Ang [XY-mean_C]	50	sLBP(1,51) [YZ-max_A]	82	FFT(1,1)-Abs [XZ-max_A]
19	sLBP(1,9) [XY-max_A]	51	sLBP(1,24) [XY-mean_A]	83	cLBP(1,10) [XY-max_C]
20	Contrast-K [XY-mean_A]	52	cLBP(1,24) [XY-mean_B]	84	FFT(1,1)-Abs [XY-max_A]
21	sLBP(1,2) [XY-max_A]	53	$\tilde{w}(7,6)$ [XY-mean_A]	85	Tx(12,1)-Mean [XY-max_B]
22	cLBP(1,29) [XY-max_C]	54	sLBP(1,46) [XY-max_C]	86	sLBP(1,16) [XY-max_B]
23	sLBP(1,23) [XY-max_C]	55	cLBP(1,11) [XZ-max_A]	87	sLBP(1,3) [XZ-max_A]
24	sLBP(1,48) [XY-max_B]	56	sLBP(1,56) [XY-max_C]	88	cLBP(1,23) [YZ-max_A]
25	sLBP(1,51) [XZ-max_A]	57	cLBP(1,2) [XY-max_C]	89	cLBP(1,26) [XY-max_B]
26	sLBP(1,47) [XZ-max_A]	58	cLBP(1,30) [XZ-mean_A]	90	sLBP(1,1) [XY-max_C]
27	sLBP(1,51) [XY-max_B]	59	cLBP(1,2) [XZ-mean_A]	91	sLBP(1,25) [XY-max_C]
28	sLBP(1,7) [XY-max_A]	60	sLBP(1,57) [XZ-mean_A]	92	sLBP(1,20) [XY-max_A]
29	sLBP(1,36) [XY-mean_A]	61	sLBP(1,28) [XY-mean_C]	93	sLBP(1,47) [XY-mean_B]
30	$\tilde{w}(4,7)$ [XY-mean_A]	62	cLBP(1,28) [XY-mean_A]	94	sLBP(1,33) [XZ-max_A]
31	FFT(1,1)-Ang [XY-mean_C]	63	cLBP(1,4) [YZ-mean_A]	95	sLBP(1,38) [XY-max_C]
32	sLBP(1,15) [XY-mean_B]	64	cLBP(1,14) [XY-mean_C]		

- $Tx(k,p)$ -(Mean, Range): Haralick texture features, where k is the texture type and p is the number of neighbor pixels.
- cLBP(d,h): Classic local binary patterns semantic. sLBP(d,h): Semantic local binary patterns. Where d is the number of compared pixels with h – neighboring pixels.
- $\tilde{w}(a,b)$: Gabor filters, where a is the frequency number, and b is the number of orientations.
- FFT(ω_0, T_0)-(Abs, Rad): Fourier-Based textural features, where ω_0 is the frequency number, and T_0 is the period. FFT(ω_0, T_0)-Abs represents the mean magnitude-value of Fourier transformed image, and FFT(ω_0, T_0)-Rad indicates the mean phase-value of Fourier transformed image.
- Between brackets [] are the different CT images used to extract features (XY-mean_type = XY-plane-slice mean images, YZ-mean_type = YZ-plane-slice mean image, XZ-mean_type = XZ-plane-slice mean image, XY-max_type = XY-plane-slice maximum image, YZ-max_type = YZ-plane-slice maximum image, and XZ-max_type = XZ-plane-slice maximum image). Image type is also included where A = Originally acquired CT-images, B = Contrast-enhanced-CT-image, and C = Contrast-enhanced plus noised-reduced-CT-image.

Table 3. Classifier performance using the ninety-five selected features (*m*) from with a 4-fold cross-validation

ROI	Classifier	2-classes		
		Mean	UCI ¹	LCI ²
1-Whole	LDA	77.6	79.8	75.6
	ANN-Softmax	73.8	74.8	73.0
	ANN-linear	73.2	74.6	72.1
	QDA	72.8	73.0	72.6
	ANN-Logistic	72.2	74.2	70.6
	MD	70.5	73.6	68.4
2- Xylem	LDA	75.7	77.1	74.4
	ANN-Softmax	71.7	72.7	70.1
	QDA	71.6	73.9	69.5
	ANN-linear	70.9	72.3	69.8
	ANN-Logistic	69.8	71.7	68.2
	MD	67.9	70.6	66.1
3- Vascular cambium	LDA*	87.9	89.2	86.6
	ANN-Softmax	80.1	82.8	78.7
	QDA	79.8	79.9	79.6
	ANN-linear	78.4	80.5	76.8
	ANN-Logistic	77.4	79.0	75.3
	MD	76.8	80.0	74.4
4- Phloem	LDA	79.2	80.9	77.6
	ANN-Softmax	76.1	77.7	74.8
	QDA	75.3	75.7	74.9
	ANN-linear	75.3	77.3	73.7
	ANN-Logistic	74.3	77.1	72.2
	MD	72.4	76.1	69.8

¹Upper Confidence interval

²Lower Confidence interval

*Classifier with highest performance

Figure captions

Fig. 1. Procedure used to generate the pattern classification algorithm to detect the presence of undesirable fibrous tissue in carrots using CT images. Figure is partially presented in color.

Fig. 2. (a) Measuring arrangement of the GE (GE Healthcare, Buckinghamshire, England, Great Britain) BrightSpeed™ RT 16 Elite CT scanner used in the study. (b) Schematic representation of a scanning of the CT system containing several 2D CT images (slices) with a distance between slices equal to the slice thickness (d), representing a 3D data block (stack). t_1 and t_n show the first and last acquired slices from the stack, respectively. Figure is partially presented in color.

Fig. 3. (a) 3D virtual cross-sections representation of a carrot at three planes (different angular orientations) along the horizontal (X), vertical (Y), and longitudinal (Z) axes (Figure not to scale). (b) Reconditioned (re-sliced) CT YZ-plane-slices. (c) Original series of acquired CT XY-plane-slices. (d) Re-sliced CT XZ-plane-slices.

Fig. 4. (a) Mean intensity values of pixels in all of the YZ-plane-slice of the whole board containing carrots. (b) Mean intensity values of pixels in all of the YZ-plane-slices for the first carrot row. (c) Mean intensity values of pixels in all of the XY-plane-slices for the first carrot row. (d) Mean intensity values of pixels in all of XZ-plane-slices for the first carrot row. Mean intensity values of pixels in final CT cropped carrot for the (e) XY-, (f) YZ- and (g) XZ-plane-slices. From (a) - (d) the beginning of the first carrot row ($Z1$ -), the end of the row ($Z2$ -), the left side ($X1$ -), the right side ($X2$ -), the bottom ($Y1$ -) and the top ($Y2$ -) of the first carrot -spatial-location-values are shown in red. Cropped sample surrounded by a red rectangle. Figure is partially presented in color.

Fig. 5. (a) Fibrous-free and (b) carrot containing undesirable fibrous tissue with their corresponding maximum CT image (XY-plane-slice). (1) Local Binary Pattern (LBP) transformations using different pixel comparison (d, h) was applied to the maximum CT image. (2) Maximum CT image Gabor filtered transformed images ($I_{rs}(i, j)$) at different scales (r) and orientation (s) for an $\theta = 45^\circ$ are included. (3) Example of an Inverse Fourier Transformation (FFT) using a frequency and period values equal to 2. $FFT_{(2,2)}$ -Abs represents the magnitude-value of Fourier transformed image, and $FFT_{(2,2)}$ -Rad indicates the phase-value of Fourier transformed image. (4) Example of Haralick textural (T_x) features, contrast and intensity features obtained from included maximum CT image. For visual reference, a fresh color image slice of the evaluated carrots are included. Figure is partially presented in color.

Fig. 6. (a) Sample distribution used to train and validate the 2-class-classifier. (b) Percentage (%) of fiber distribution and box-plot for carrots containing undesirable fibrous tissue (class-1). (c) In the box-plot represents the class-1 overall mean % of fiber. (d) Linear discriminant analysis (LDA) classifier performance from segmented vascular cambium (ROI) using cross-validation with 4-fold in relation to the number of m . Black line represents the classification mean performance, dotted black line (---) represent 95% confidence intervals for the cross-validation classification pool. (e) Validation confusion matrix corresponding to the carrot quality class using 25% of samples with 95- m (overall accuracy rate equal to 87.9%). Figure is partially presented in color.

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