Postharvest noninvasive assessment of fresh chestnut (Castanea spp.) internal decay using computer tomography images

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Abstract

X-ray computed tomography (CT) is an effective noninvasive tool to visualize fresh agricultural commodities’ internal components and quality attributes, including those of chestnuts (Castanea spp.). There is no reported procedure to automatically, effectively and efficiently classify fresh commodities from a continuous inline flow through a CT system. If the information obtained by CT scanning of fresh agricultural commodities is to be used in an industrial application (e.g. inline sorting), automated interpretation of CT images is essential. For this purpose, an image analysis method (algorithm) for the automatic classification of CT images obtained from 2848 fresh chestnuts (cv. ‘Colossal’ and ‘Chinese seedlings’), during the harvesting years from 2009 to 2012, was developed and tested. Classification accuracy was evaluated by comparing the classes obtained from six CT images per chestnut to their internal quality assessment. Internal quality assessment was conducted by an experienced human rater by visually and invasively rating fresh chestnut internal decay severity (quality) into 5-, 3- and 2- classes.

After CT image preprocessing, cropping and segmentation, 1194 grayscale intensity and textural features were extracted from the six CT images per sample. Relevant features were selected using a sequential forward selection algorithm with the Fisher discriminant objective function. 86, 155 and 126 features were effective in designing a quadratic discriminant classifier with a 4-fold cross-validation. Performance accuracy of 85.9 %, 91.2 % and 96.1 % for 5, 3 and 2 classes was found, respectively. Results show that this method is accurate, reliable, and objective in determining fresh chestnut internal quality, and it is applicable to an automatic noninvasive inline CT sorting system.

Keywords: Nondestructive, quality, classification, computer vision

1 Introduction

Noninvasive techniques (color vision) are employed to determine external quality attributes (peel color, external defects and shape) in fresh produce (Mery & Pedreschi 2005; Brosnan & Sun 2004; Blasco, Aleixos, & Molto 2007; Moreda et al., 2012; Gomes & Leta 2012). In addition, techniques based on optical, magnetic resonance imaging (MRI), two-dimensional (2D) X-ray, near-infrared (NIR), vibration, sonic and ultrasonic, have also been explored for non-destructive determination of internal produce quality attributes (Cubero et al., 2010; Lorente et al., 2011; Milczarek et al., 2009). NIR spectroscopy has been successfully used to
detect hidden insect damage in chestnuts (Moscetti et al., 2014), but NIR has not been proven to be successfully detect chestnut internal decay. Thus, there is a need to develop an in vivo inline nondestructive tool capable of better assessing fresh agricultural commodity internal attributes, including chestnuts. This will enable the fresh commodity industry to offer better quality products, therefore increasing customer satisfaction, opening new market opportunities, and lessening customer complaints (Donis-González et al., 2012a; Nicolai et al., 2007; Sornsrivichai, Yantarasri, & Kalayanamitra 2000).

Computer tomography (CT) has been demonstrated as an effective noninvasive internal characteristic off-line diagnostic tool in agriculture. Postharvest internal evaluation of several fresh produce has been recently shown to be achievable. Donis-González et al. (2012a; 2012b) found a significant relationship between fresh chestnut CT images and their internal components, including the presence of decayed tissue. Jha et al. (2010) described the potential of nondestructive techniques, including CT, to measure mango (Magnifera indica) internal quality (i.e. size, shape, pulp and moisture). There is no available procedure reported to automatically, and effectively classify fresh agricultural commodities from a continuous inline flow of entities going through a CT scanning system.

The objective of this study was to describe the methodology for developing an automated classification algorithm to detect internal decay in CT images of fresh chestnuts that would be suitable for an inline CT inspection system.

2 Materials and methods

2.1 Sample collection and preparation

Steps used to generate the pattern classification algorithm to categorize chestnut quality using CT images are illustrated in Fig. 1. A total of 1424 physiologically mature Chinese seedlings (C. mollissima) and 1424 (C. sativa x C. crenata) cv. 'Colossal' chestnuts were obtained from Chestnut Growers Inc. (CGI; Grand Haven, Michigan, USA) (Total of 2848). Chestnuts were collected from 7 commercial farms in Michigan. Equal numbers of chestnuts were collected every year, from the 2009 to the 2012 season (September-October). Samples were postharvest treated, prepared, and stored as described in Donis-González et al. (2012b).

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, UK) as described in Donis-González et al. (2012). Scanning parameters were optimized using the procedure in Donis-González et al. (2012). 2D CT images were acquired every 2.5 mm (d), at a voltage, current, and image resolution (XY plane) equal to 120keV, 170mA, and 1.42 px/mm respectively.

2.3 CT image preprocessing and re-slicing

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 (http://www.mathworks.com), and in R V2.10.0 (http://cran.r-project.org/). 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.iing.puc.cl/index.php/balu/). Depending on chestnut physical size, each chestnut contains between 8 to 17 XY-plane-slices representing virtual cross-sections of a chestnut along the longitudinal (Z) axis. Using a process known as re-slicing (Bushberg et al., 2002), originally acquired XY-plane-slices from several chestnut can be reconditioned into two different planes, resulting in a series of YZ- and XZ-plane-slices containing between 8 to 17 virtual slices.

¹BrightSpeed® is a registered trademark of General Electric Healthcare.
2.3.1 Individual chestnut CT image cropping

Chestnut rows and individual chestnuts were cropped from the overall CT data set containing the scanning table, volume of air and other chestnuts, by visually/manually determining their spatial location (red values), as shown in Fig. 2. An automatic cropping/recognition algorithm should be applied, if an inline system is used.

For each chestnut that is re-sliced making up the three different planes, a data set of approximately 50 raw CT image slices of about 50 x 50 pixels each (depending on chestnut physical size) are generated. For further analysis, data set dimensionality is then reduced from these original 50 raw CT images per chestnut sample to 6 resultant CT images per sample (resultant image set – Fig. 1). Three mean and three maximum intensity value CT images from the three different planes (XY, XZ and YZ) are obtained per chestnut sample (total of 6) as seen in Fig. 2e-2j. Mean and maximum intensity images were used for internal quality classification as they visually relate to fresh chestnut internal characteristics (Donis-González et al. 2012).

2.3.2 Contrast enhancement and images segmentation (Binary mask)

Contrast enhancement is a vital step in image processing, and it is done to increase image quality (Jagannath, Virmani, & Kumar 2012). In this study, sets of image preprocessing steps were implemented to increase CT image contrast, before classification, in the resultant 6 images per chestnut (Section 2.3.1), as described in Wirth et al. (2004) and Nixon & Aguado (2008). Image segmentation is implemented to recognize the region of interest in an image (chestnut in each CT image). CT image segmentation was done by using the balanced histogram thresholding method, as described in Anjos and Shahbazkia (2008).
2.4 Visual based fresh chestnut quality and internal component assessment

Immediately after CT scanning, each fresh chestnut was transversely sliced in 4 sections using a sharp hand knife. Slice sizes varied depending on chestnut size, but typically were between 5 to 7.5 mm thick. All internal kernel faces in between each slice (total of 6) were color scanned and then qualitatively assessed for disorders, void spaces, and embedded pellicle as seen in Donis-González et al. (2013; 2012).

2.5 Feature extraction and selection

Features were extracted from the six contrast enhanced 16-bit CT resultant intensity images per chestnut, as previously described in Sections 2.3.1 and 2.3.2. A total of 199 features were extracted per CT image, and then features from the six CT images were concatenated to form a feature vector (x) with 1194 components, as partially illustrated in Fig. 1. Extracted features per CT image included: (1) 6 basic intensity features (Mery et al., 2011; Nixon & Aguado 2008; Shapiro & Stockman 2001), (2) 26 Haralick textural (Tx) features (Haralick 1979; Mery et al., 2010; Donis-González et al. 2013), (3) 95 intensity local binary pattern (LBP) features (Ojala, Pietikäinen, & Maenpää 2002; Ahonen et al., 2009; Chai et al., 2013; Pietikäinen, Ojala, & Xu 2000), (4) 67 Gabor intensity textural features (Kumar & Pang 2002; Ng, Guojun, & Dengsheng 2005; Mery & Soto 2008; Zhang 2002; Zhu et al., 2007), and (5) 5 contrast features (Kamm 1998; Mery & Filbert 2002; Mery 2001).

After feature extraction, the best features to train the classifier (Mery & Soto 2008) were selected. The purpose of this step, is to obtain a smaller subset of features (m) from the original data set (x), which yield the highest classification rate (Jain, Duin, & Jianchang 2000).

In this study, the sequential forward selection (SFS) technique (algorithm), taking feature dependencies into account (eliminates features that are highly correlated r ≥ [0.95]) (Silva, Siqueira, & Calóba 2002), was selected as a search strategy (Jain, Duin, & Jianchang 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, Hart, & Stork 2000), (2) linear discriminant analysis (LDA) (Duda, Hart, & Stork 2000; Quanquan, Zhenhui, & Jiawei 2011), and (3) quadratic discriminant analysis (QDA) objective functions (Bishop 2007; Jain, Duin, & Jianchang 2000).

2.6 Classification (training and validation)
A supervised learning approach was used to train the pattern classification algorithm (Duda et al., 2000). Supervised classes, known as labels, were based on 5-, 3- and 2-categorical groups, where each chestnut was invasively categorized into 5-, 3- or 2-quality-classes, based on their internal disorder (decay) severity level (Donis-González, Guyer, & Pease 2012; Donis-González et al. 2013).

Using the selected features \( (m) \), decision boundary lines, planes, and hyper planes were implemented using LDA, QDA, Mahalanobis distance (MD) (Duda, Hart, & Stork 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). Performance of each of the classifiers was measured as the correctly classified chestnuts, using the set of 6 CT images, in reference to its supervised categorical class (label).

3 Results and discussion

In this study, the features were reduced from 1194 to 96 (5-class classifier), 155 (3-class classifier) and 126 (2-class classifier) features. The SFS with the Fisher discriminant objective function \( (J(W)) \) method offered the most powerful features, yielding the best classifier performance. The other feature selection methods, using addition objective functions (Section 2.7) performed poorly (Results not shown). The most important features for classification mainly include textural features (approximately 88%) including: (1) LBP features, (2) \( T_x \) and contrast features, and (3) Gabor features at different scale and orientation, acquired from the different CT images. Less influential, about 12% of the utmost important features involve the basic intensity features.

![Figure 3](image.png)

**Figure 3:** (a) Sample distribution used to train and validate the 5-class classifier with example color images. (b) QDA classifier performance. Black line represents the classification mean performance, dotted black line \((---)\) represent 95% confidence intervals for the cross-validation classification pool. (c) Validation confusion matrix corresponding to the chestnut quality class prediction using 25% of samples with 96-m (overall accuracy rate equal to 85.9%).

The best overall classifier is the QDA classifier. Other classifiers were tested, however the overall classification performance was lower (Results not shown). Performance results for 5-classes, using the selected QDA classifier, for increasing number of features \( (m) \), are included in Fig. 3b. Results for 3- and 2-classes are not included. Performance increases in relation to an increase in \( m \). Fig. 3c shows the confusion matrix corresponding to the overall QDA classifier performance for 5-classes.

4 Conclusions

After CT imaging, 6 resultant CT images were preprocessed (contrast enhancement) and segmented. Thereafter, a total of 1194 grayscale intensity, and textural features were ex-
tracted. SFS was carried out to reduce the dimensionality of the total image-extracted features. Ultimately, 96, 155 and 126 features were found to be effective in designing a QDA classifier with a 4-fold cross-validated overall performance accuracy of 85.9%, 91.2% and 96.1% for 5, 3 and 2 classes, respectively.

5 Acknowledgements

This work was financially supported by Ernie & Mabel Rogers Endowment & Project GREEEN at MSU. The authors thank Mr. Mario and Mr. James Burns for their valuable support. Mr. Mark Sellers, Mr. Rex Miller, and Ms. Meg Willis-Redfern for technical support using the CT scanner, and the MSU Veterinary Hospital for providing the CT scanner.

6 References


