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Robustness of near infrared spectroscopy based spectral features for non-destructive bitter pit detection in honeycrisp apples

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ABSTRACT

Bitter pit is a serious disorder in apples. The current technique involves manual inspection of fruits prior to packaging for fresh market. Therefore, the main objective of this study was to evaluate the near infrared (NIR) spectroscopy for bitter pit detection in apples. The spectral reflectance data were collected from healthy and bitter pitted honeycrisp apples from two different locations. Apples were stored in cold storage and spectra were acquired at 0, 35 and 63 days after harvest (DAH). On each of the DAH, each of the 40 apples (20 healthy and 20 bitter pitted) were analyzed to acquire three spectra per location with three marked locations per fruit. Suitable spectral features were selected using stepwise multilinear regression and rank feature technique. The spectral bands of 971.2, 978.0, 986.1, 987.3, 995.4, 1131.5, 1135.3, 1139.1 and 1142.8 nm were identified as the bands thought to be associated with bitter pit in honeycrisp apples. Feature datasets were evaluated using quadratic discriminant analysis and support vector machine classifiers to evaluate robustness of these features in bitter pit detection. Overall, classifiers performance comparison revealed that bitter pitted honeycrisp apples can be distinguished with average accuracy in the range of 78–87%. Based on spectral features of this study, spectra related to cell membrane water-soaked regions that contribute to spectral variation might have been identified. Our on-going studies are further validating those bands on Honeycrisp and other apple cultivars and using different spectral band selection methods towards developing a portable sensing module for apple bitter pit detection.

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1. Introduction

Bitter pit is considered as one of the key physiological disorders in fresh market apple cultivars. It is characterized by a depression in the flesh of the fruit, commonly located in the distal portion of the fruit (do Amarante et al., 2013). Affected fruit has dark spots, which occur on the skin and/or in the flesh. The cells in these spots are necrotic, and turn into brownish-black. Although specific reasons for apple bitter pit has not been found, several research studies have related apple bitter bit with Calcium (Ca) deficiency, Magnesium to Calcium (Mg/Ca) ratio and Potassium to Calcium (K/Ca) ratio (Wills et al., 1976; Ferguson et al., 1979; Saure, 1996; Rosenberger et al., 2004; do Amarante et al., 2013). During fruit storage and transport, progressive physiological disorders may arise, among which bitter pit is very prominent one. It is imperative to correctly identify fruit prone to bitter pit before export or shipment in order to prevent economical loss due to rejections later in the market (Wooldridge, 1999; Lötze, 2005) and also associated labor and packaging material costs.

Most commonly used bitter pit detection techniques that are reported in the literatures are: (1) forcing maturity using ethylene or magnesium solutions, (2) fruit mineral analysis (Ca, (K + Mg)/Ca ratio), and (3) measuring vegetative length (Burmeister and Dilley, 1993; Retamales et al., 2000). The potential for bitter pit incidence in apple fruits can increase when vegetative growth is intensive because under these conditions the Ca is diverted to shoots and leaves instead of fruit tissues (Retamales and Valdes, 1996; Atkinson et al., 2013). Above mentioned bitter pit identification techniques are destructive and time consuming. Therefore, it is critical to develop non-destructive and rapid sensing technologies to identify bitter pit on individual fruits at earlier stages in production and storage. Such detection techniques may also aid

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growers in reducing in-field crop losses by making timely decisions on appropriate management practices.

Techniques such as visible-near infrared (Vis-NIR) spectroscopy, mid-infrared spectroscopy, fluorescence spectroscopy and hyperspectral imagining are rapid, non-destructive methods and have been applied for biotic and abiotic stress detection in fruits and leaves in specialty crops (Belasque et al., 2008; Naidu et al., 2009; Qin et al., 2009; Sankaran et al., 2010; Sankaran and Ehsani, 2011). NIR-spectroscopy has been successfully used for studying quality and disorders of different tree fruits (Slaughter, 1995; McGlone and Kawano, 1998; Saranwong et al., 2004). Some of the above studies have also reported that Vis-NIR spectroscopy technique has many advantages over other destructive methods such as rapid measurement, repeatability and ability to measure multiple attributes simultaneously. Several studies have explored possibility of using Vis-NIR spectroscopy technique for detecting bruises in apples by reflection measurement (Upchurch et al., 1990; Xing et al., 2006; Xing and De Baerdemaeker, 2007; Zhang et al., 2013). However, there are very few studies reporting use of NIR-spectral data for detecting bitter pit in apples (Lötze, 2005; Nicolaï et al., 2006). Lötze (2005) classified between healthy and bitter pitted braeburn apples using fluorescence imaging with accuracy of 75–100%. Similarly, Ariana et al. (2006) used integrated imaging model of reflectance and fluorescence to differentiate between normal and bitter pitted apples (honeycrisp, redcort, and red delicious apple varieties) with higher classification accuracy of 87% for honeycrisp apple. Further research is essential for exploring the NIR spectroscopy applicability in detecting bitter pit in apples.

The main goal of the present study was to evaluate NIR spectroscopy for bitter pit detection in honeycrisp apple. Specific objectives of the study were: (1) to determine important spectral reflectance bands in near infrared region for bitter pit detection, and (2) to evaluate ability of selected spectral bands in classifying healthy and bitter pitted apples using different multivariate classification algorithms. First, stepwise multilinear regression (SMLR) and rank feature technique (RFT) was used to select the spectral features. Then, quadratic discriminant analysis (QDA) and support vector machine (SVM) based classifiers were applied for discriminating healthy and bitter pitted apples.

2. Materials and methods

2.1. Field sites and data collection

Honeycrisp apples were harvested on August 29, 2014 from two commercial orchards located at Burbank and Prescott, WA. The orchards were planted in 2007 and 2009, respectively and trees were on M-9 NIC 29 rootstock. Typical plant and row spacing were 0.91×3.65 m. From each location, apples were picked at harvest time and consisted of healthy and bitter pitted fruits (Fig. 1). Harvested apples were transported to the laboratory on same day and were stored in separate boxes with 20 fruits per condition (healthy and bitter pit) for each of the two locations. Packaged fruit boxes were stored in a controlled environment maintained at a temperature of 5 °C. The fruit was equilibrated at room/laboratory temperature for about 2 h before spectra acquisition.

The spectral reflectance data were collected under laboratory condition using portable spectroradiometer (SVC HR-1024, Spectra Vista Cooperation, NY) with measurement range of 350–2500 nm. The spectral resolution of spectroradiometer was $\leq$3.5, $\leq$9.5, and $\leq$6.5 nm for 350–1000, 1000–1850, and 1850–2500 nm wavelength ranges, respectively. A white panel (Spectralon Reflectance target, CSTM-SRT-99-100, Spectra Vista Cooperation, NY) was used to acquire reference spectra (Sankaran and Ehsani, 2011). The spectral reflectance data were measured from three different positions in an apple. Thus, sixty spectra were collected from 20 healthy and 20 bitter pitted apples for storage periods of 0, 35 and 63 d, also termed as days after harvest (DAH). As the goal was to measure non symptomatic bitter pit (without visible symptoms), the spectral data in the range of 800–2500 nm was considered for analysis.

The spectral reflectance data were analyzed as three datasets for each storage periods (total datasets = 9). Spectral data obtained from fruit samples from location −1 (Prescott, WA) and location-2 (Burbank, WA) with analysis on 0 DAH (or storage) were referred as Dataset-I and Dataset-II, respectively. Dataset I and Dataset II were combined to develop new set of data referred as Dataset-III. Similarly, Datasets IV, V, VI and Datasets VII, VIII, IX were developed for 35 and 63 DAH apples, respectively. The details on each dataset are shown in Table 1. Spectral band selection was performed on 63 DAH datasets as detailed in Section 2.2 and selected spectral bands were then used to classify 0, 35 and 63 DAH spectral datasets. Before data analysis each spectra was normalized based on Euclidean norm (Sankaran et al., 2011).

2.2. Feature selection

Feature selection was performed using two different feature extraction methods, SMLR (Matlab® R2014b) and RFT (Matlab® R2014b). For selecting useful features using SMLR, an initial model with no terms, an entrance tolerance of 0.05, and an exit tolerance of 0.10 was set. In RFT, the input features were ranked using *t*-test statistic (significance level $\alpha = 0.05$) and also weighed to remove highly correlated features (Khorramnia et al., 2014). The features were selected only for Dataset VII, VIII and IX (i.e. 63 DAH apples spectral data). The selection of these datasets for features selection

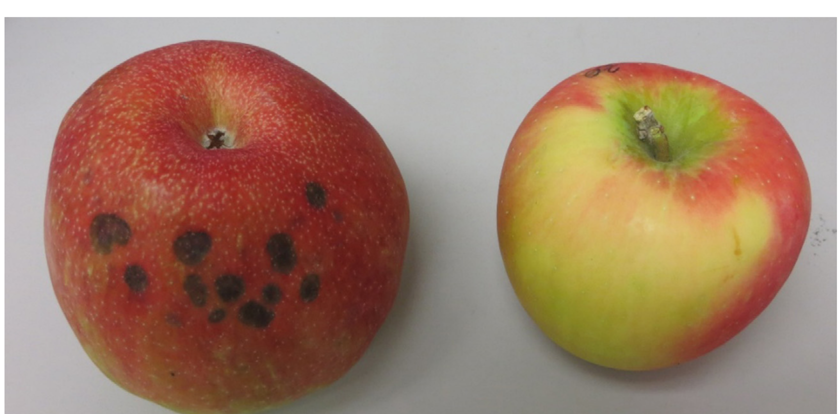

Fig. 1. Honeycrisp apples with and without bitter pits.