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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.

Table 1
Details of the datasets used in this study.

Dataset	Healthy apples spectra	Bitter pitted apples spectra	Total
0 DAH			
I	60	60	120
II	60	60	120
III	120	120	240
35 DAH			
IV	60	60	120
V	60	60	120
VI	120	120	240
63 DAH[a]			
VII	60	60	120
VIII	60	60	120
IX	120	120	240

DAH: Days after harvest.
I, IV, VII: Datasets for location-1.
II, V, VIII: Datasets for location-2.
III, VI, IX: Combined datasets for location-1 and -2.
[a] Used for feature selection.

was based on previous study results which reported significant bitter pit progression inside the fruits during 63 d of storage (Jarolmasjed et al., 2016). After extracting the important spectral bands, the common spectral bands for both the methods (SMLR and RFT) were selected from each dataset as reported in the previous studies (Sankaran and Ehsani, 2011; Khorramnia et al., 2014) and were labeled as Bands-1, Bands-2 and Bands-3. Bands-1, −2 and −3 were combined to form Bands-4. Similar to this study, Sankaran and Ehsani (2011) also reported a formation of fourth set of spectral bands using the selected spectral bands from all the base datasets. Combined bands (Bands-4) were expected to be highly effective than all other three bands in predicting bitter pit in apples because it includes all the bands that are common to each feature selection methods and bands selected for each of the three datasets. Bands-4 obtained using 63 d storage spectral features were only used for developing the classifying models for 0, 35 and 63 d stored apples. Classification datasets are henceforth represented as individual locations (Location-1 and Location-2) and combined spectral data for both locations (Combined locations) for respective 0, 35, 63 DAH (or storage) conditions.

2.3. Classification

Two different classification algorithms (QDA and SVM) were used to evaluate selected features (Matlab® R2014b) suitability in discriminating two different classes of apples. Total of nine datasets were formulated using above spectral bands and were used to train and test the classifiers. Each dataset was separated into the balanced training and testing dataset (training: testing = 50:50, 70:30, 85:15). The QDA and SVM classifier training involved fivefold cross-validation (K-fold = 5) to derive the best model that was used for classifying test dataset. In this study, K-fold = 5 was chosen instead of K-fold = 10 (default) in order to maintain the number of observations used for cross validating the trained models ≥10 for each of the training to testing ratios. Independent train:test ratios were to understand effect of training dataset size on the classifier performance. A nonlinear radial basis function (RBF) as the kernel was used to develop the SVM model (similar to Khorramnia et al., 2014).

Each classifier was trained and tested three times on each dataset by randomizing the feature dataset as described by Sankaran and Ehsani (2011). Three different sets of random numbers were created and for each dataset same set of random numbers were used. The classification accuracies (healthy apples-HA, bitter pit apples-BPA and overall) reported are average of three test runs on each dataset.

2.4. Statistical analysis

ANOVA was performed using SAS®9.2 at the significance level (α) of 0.05 to determine whether the QDA and SVM classifier models yielded different accuracies of classification and to determine if classification accuracies are different for HA, BPA and overall. Similarly, ANOVA was also performed to study the effect of varying training to testing sample ratios and location on classification accuracies. The least significant differences (LSD) between treatment means were calculated using Fisher's test in order to determine which ones are significantly different from each other (Kafle et al., 2016).

3. Results and discussion

3.1. Feature selection

The features selected using SMLR and RFT feature selection techniques for Dataset VII, VIII and IX are shown in Table 2. Similarly, the spectral bands that are common to both feature selection techniques are summarized in Table 3 for each dataset (Bands-1, Bands-2, Bands-3). Bands-4 which was developed including all the spectral bands of Bands-1, Bands-2 and Bands-3 includes 971.2, 978.0, 986.1, 987.3, 995.4, 1131.5, 1135.3, 1139.1 and 1142.8 nm. Thus, features in the range of 970–995 nm and 1130–1143 nm were selected as suitable features for better discrimination of the healthy and bitter pitted apples. Prior works have reported that water bands are effective in discriminating the defects (bruises, bitter pit, etc.) in apple (Williams and Norris, 2001; Lötze, 2005; Nicolaï et al., 2006; Gómez et al., 2006). Among nine selected features in Bands-4, five of the features (971.2, 978.0, 986.1, 987.3, 995.4 nm) represent water bands. Gómez et al. (2006) explained that a strong water absorption band exists in the range of 960–990 nm and Lötze (2005) reported 1164, 1417, 1830 and

Table 2
Selected features using stepwise multilinear regression (SMLR) and rank feature technique (RFT) for 63 d storage apples based spectral datasets.

Dataset	Feature extraction method	Selected wavelengths (nm)
VII	SMLR	1139.1
	RFT	971.2, 975, 1127.7, 1131.5, 1135.3, 1139.1, 1142.8, 1146.6, 1150.4, 1154.2, 1158, 1161.8, 1165.6, 1169.4, 1173.2, 1176.9, 1180.7, 1184.5, 1188.3, 1192.1
VIII	SMLR	936.3, 939.8, 941, 942.1, 966.4, 967.6, 968.8, 978, 986.1, 987.3, 995.4, 1009.5, 1386.9, 1719.5, 1741
	RFT	952.5, 973.4, 974.5, 975.7, 976.8, 978, 979.2, 981.5, 982.6, 983.8, 985, 986.1, 987.3, 988.4, 994.2, 995.4, 996.6, 997.7, 998.9, 1000.1
IX	SMLR	808.9, 878.2, 971.2, 1070.6, 1085.8, 1093.5, 1116.3, 1131.5, 1135.3, 1142.8, 1154.2, 1158, 1331.1, 1383.2, 1705.2, 1708.8, 1726.7, 1840.6, 1844.2, 1847.7, 2268.1, 2280,2284.7, 2315.1, 2506
	RFT	971.2, 975, 978.8, 982.7, 1127.7, 1131.5, 1135.3, 1139.1, 1142.8, 1146.6, 1195.8, 1199.6, 1203.4, 1207.2, 1210.9, 1214.7, 1218.5, 1222.2, 1226, 1233.5

Table 3
Selective common spectral bands from different sets of spectral features reported in Table 2.

Spectral bands	Wavelengths (nm)
Band−1[a]	1139.1
Band−2[b]	978, 986.1, 987.3, 995.4
Band−3[c]	971.2, 1131.5, 1135.3, 1142.8
Band−4[d]	971.2, 978, 986.1, 987.3, 995.4, 1131.5, 1135.3, 1139.1, 1142.8

[a] From Dataset VII.
[b] From Dataset VIII.
[c] From Dataset IX.
[d] From Dataset VII, VIII & IX.

1930 nm as water related bands that may have improved discrimination between bitter pitted and healthy apples.

Evaluation of spectral data obtained from 63 DAH samples revealed that healthy fruits had higher reflectance than bitter pit affected apples as reported by Lötze (2005). According to Simon (1978) if the calcium deficiency exists in apple fruits, the cell membranes are dis-organized and it might results in appearance of water-soaked regions which finally turns out as lesions that are visible in apple fruit as bitter pit and on apple leaves as necrotic spots. Similarly, Lötze (2005) explained that pitted lesions in infected apple may increase the light scattering as a result of dehydration compared to healthy tissue in the healthy apple. Brown et al. (1974) and Woolley (1971) also support the decrease in NIR-reflectance for the plant/fruit tissues with decrease in water contents.

Table 4
Overall and individual class classification accuracies using selected spectral bands (Band-4 as reported in Table 3).

Dataset	Class	Classification accuracy ([Average (Std. Dev.)], %)					
		0 DAH		35 DAH		63 DAH	
		QDA	SVM	QDA	SVM	QDA	SVM
Train: Test = 50:50							
Location-1	HA	86(5)	76(12)	84(3)	80(9)	93(3)	97(3)
	BPA	78(2)	71(15)	80(10)	73(11)	97(3)	81(8)
	Overall	82(3)	71(1)	82(4)	76(8)	96(1)	89(4)
Location-2	HA	74(4)	80(20)	99(2)	99(2)	85(5)	93(4)
	BPA	99(2)	60(21)	90(1)	63(10)	85(5)	65(2)
	Overall	87(2)	69(2)	94(1)	80(6)	86(1)	78(3)
Combined	HA	82(3)	61(10)	78(11)	74(6)	91(4)	89(9)
	BPA	83(3)	78(3)	76(16)	77(6)	77(8)	76(4)
	Overall	83(3)	69(5)	76(3)	76(1)	73(12)	83(3)
Train: Test = 70:30							
Location-1	HA	93(7)	76(6)	82(16)	81(12)	91(8)	96(8)
	BPA	81(5)	80(9)	87(5)	77(13)	98(3)	78(6)
	Overall	87(2)	78(3)	84(8)	79(4)	94(6)	88(4)
Location-2	HA	90(9)	72(20)	94(0)	100(3)	92(3)	83(6)
	BPA	93(6)	73(11)	87(6)	63(4)	92(7)	77(12)
	Overall	92(3)	70(12)	91(3)	82(2)	93(4)	81(5)
Combined	HA	81(9)	65(8)	82(4)	80(5)	92(2)	89(3)
	BPA	82(7)	78(4)	78(10)	74(9)	78(7)	82(5)
	Overall	81(1)	72(2)	80(3)	77(6)	85(4)	86(2)
Train: Test = 85:15							
Location-1	HA	87(11)	79(7)	97(5)	83(8)	96(7)	92(7)
	BPA	83(7)	83(18)	76(21)	64(15)	91(8)	79(10)
	Overall	85(8)	80(8)	87(6)	76(3)	96(3)	85(3)
Location-2	HA	96(3)	74(16)	97(5)	93(12)	83(8)	78(16)
	BPA	100(0)	67(3)	90(17)	57(19)	97(6)	68(11)
	Overall	96(3)	70(8)	93(8)	76(3)	89(6)	74(3)
Combined	HA	81(14)	80(11)	95(5)	80(16)	96(3)	91(6)
	BPA	92(7)	80(9)	70(9)	77(12)	74(8)	74(16)
	Overall	84(9)	79(2)	82(4)	78(3)	85(4)	82(8)

HA: Healthy apple; BPA: Bitter pitted apple.

3.2. Classification

The average individual (HA and BPA) and overall classification accuracies for different storage periods (0, 35, 63 d) using different classifier models (QDA, SVM) at different training to testing sample ratios are summarized in Table 4. The average overall classification accuracies for QDA and SVM classifiers were in the range of 73–96% (87% ± 11%) and 69–89% (78% ± 9%), respectively. ANOVA analysis showed classification accuracies using QDA classifier were significantly different compared to SVM classifier. Sankaran et al. (2011b) reported that QDA had higher classification accuracies among other classifiers such as linear discriminant analysis (LDA), k-nearest neighbor, and soft independent modeling of classification analogies (SIMCA). But in the study conducted by Khorramnia et al. (2014), SVM classifier showed higher prediction accuracies for nutrients composition (N, P, K, Mg, Ca and B) of oil palm leaf compared to SIMCA and artificial neutral network (ANN) classifiers. Although in the present study, QDA was found to yield higher accuracies than SVM for classifying the healthy and bitter pitted apples, further study with the larger datasets need to be performed for validating this aspect because arguably algorithm performance depend on several factors, which might be responsible for very different results, case by case as reported in the previous studies (Sankaran and Ehsani, 2011; Khorramnia et al., 2014).

Classification accuracies were significantly higher for HA compared to BPA and overall. The classification accuracies for 63 d storage apples were calculated to be significantly higher than for 35 d and 0 d storage apples. The increase in bitter pit area with the storage time and use of selected bands from spectra of 63 d storage apples could be the reason for showing higher accuracies for the 63 d storage apples. No significant difference in classification accuracies was found for different locations. It was also observed that the classification accuracies did not change significantly by changing the training to testing sample ratios (50:50, 70:30, and 85:15). Similar to this study, Sankaran et al. (2011) also did not notice any significant change in classification accuracies of diseased citrus fruits (Huanglongbing) when varying training to testing sample ratios.

Overall, selected spectral features satisfactorily discriminated between healthy and bitter pitted apples. Thus, results indicated that the NIR-spectroscopy method offers potential for non-destructive discrimination of bitter pitted apples from healthy ones. The results from this research could be used to develop an automatic apple sorting system.

4. Conclusions

This study evaluated the applicability of using NIR reflectance spectra for detecting bitter pit in honeycrisp apples. The spectral reflectance data obtained in the range of 970–996 nm and 1130–1143 nm represented variation in healthy and bitter pitted apples. QDA and SVM based classification of spectral datasets had overall classification accuracy of 87% ± 11% and 78% ± 9%, respectively. Overall, results indicated that both of the multivariate non-linear classifiers, QDA and SVM can be used in discriminating healthy and bitter pitted apples and trends confirm on the applicability of using NIR reflectance spectra for the detection of bitter pit in apples.

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References

Ariana, D., Guyer, D.E., Shrestha, B., 2006. Integrating multispectral reflectance and fluorescence imaging for defect detection on apples. Comput. Electron. Agric. 50 (2), 148–161.
Atkinson, D., Jackson, J.E., Sharples, R.O., 2013. Mineral Nutrition of Fruit Trees: Studies in the Agricultural and Food Sciences. Elsevier.
Belasque, L., Gasparoto, M.C.G., Marcassa, L.G., 2008. Detection of mechanical and disease stresses in citrus plants by fluorescence spectroscopy. Appl. Opt. 47, 1922–1926.
Brown, G.K., Segerlind, L.J., Summitt, R., 1974. Near-infrared reflectance of bruised apples. Trans. ASAE 17, 17–19.
Burmeister, D.M., Dilley, D.R., 1993. Prediction of bitter pit on apples using Mg^{2+} salt infiltration to induce bitter pit-like symptoms. HortScience 28 (5) 446–446.
do Amarante, C.V.T., Miqueloto, A., de Freitas, S.T., Steffens, C.A., Silveira, J.P.G., Corrêa, T.R., 2013. Fruit sampling methods to quantify calcium and magnesium contents to predict bitter pit development in 'Fuji'apple: a multivariate approach. Sci. Hortic. 157, 19–23.
Ferguson, I.B., Reid, M.S., Prasad, M., 1979. Calcium analysis and the prediction of bitter pit in apple fruit. N. Z. J. Agric. Nes. 22 (3), 485–490.
Gómez, A.H., He, Y., Pereira, A.G., 2006. Non-destructive measurement of acidity, soluble solids and firmness of Satsuma mandarin using Vis/NIR-spectroscopy techniques. J. Food Eng. 77 (2), 313–319.
Jarolmasjed, S., Espinoza, C.Z., Sankaran, S., Khot, L.R., 2016. Postharvest bitter pit detection and progression evaluation in 'Honeycrisp' apples using computed tomography images. Postharvest Biol. Technol. 118, 161–167.
Kafle, G.K., Zhou, J., Bahlol, H.Y., Khot, L.R., 2016. Towards precision spray applications to prevent rain-induced sweet cherry cracking: understanding calcium washout due to rain and fruit cracking susceptibility. Sci. Hortic. 203, 152–157.
Khorramnia, K., Khot, L.R., Ehsani, R., Shariff, A.R.B.M., Mansor, S.B., Rahim, A.B.A., 2014. Oil palm leaf nutrient estimation by optical sensing techniques. Trans. ASABE 57 (4), 1267–1277.
Lötze, E., 2005. Pre-Harvest Determination of Bitter Pit Potential in Apples. Dept. of Horticultural Sciences, University of Stellenbosch (Ph.D. Dissertation).
McGlone, V.A., Kawano, S., 1998. Firmness, dry-matter and soluble-solids assessment of postharvest kiwifruit by NIR spectroscopy. Postharvest Biol. Technol. 13 (2), 131–141.
Naidu, R.A., Perry, E.M., Pierce, F.J., Mekuria, T., 2009. The potential of spectral reflectance technique for the detection of Grapevine leafroll-associated virus-3 in two red-berried wine grape cultivars. Comput. Electron. Agric. 66, 38–45.
Nicolaï, B.M., Lötze, E., Peirs, A., Scheerlinck, N., Theron, K.I., 2006. Non-destructive measurement of bitter pit in apple fruit using NIR hyperspectral imaging. Postharvest Biol. Technol. 40 (1), 1–6.
Qin, J., Burks, T.F., Ritenour, M.A., Bonn, W.G., 2009. Detection of citrus canker using hyperspectral reflectance imaging with spectral information divergence. J. Food Eng. 93, 183–191.
Retamales, J.B., Valdes, C., 1996. Avances en la prediction de bitter pit en manzanas. Rev. Fruticola 17 (3), 93–97.
Retamales, J.B., Valdes, C., Dilley, D.R., 2000. Bitter pit prediction in apples through Mg infiltration. Acta Hortic. 512, 169–179.
Rosenberger, D.A., Schupp, J.R., Hoying, S.A., Cheng, L., Watkins, C.B., 2004. Controlling bitter pit in honeycrisp' apples. HortTechnolog 14 (3), 342–349.
Sankaran, S., Ehsani, R., 2011. Visible-near infrared spectroscopy based citrus greening detection: evaluation of spectral feature extraction techniques. Crop Prot. 30 (11), 1508–1513.
Sankaran, S., Ehsani, R., Etxeberria, E., 2010. Mid-infrared spectroscopy for detection of Huanglongbing (greening) in citrus leaves. Talanta 83 (2), 574–581.
Sankaran, S., Mishra, A., Maja, J.M., Ehsani, R., 2011. Visible-near infrared spectroscopy for detection of Huanglongbing in citrus orchards. Comput. Electron. Agric. 77 (2), 127–134.
Saranwong, S., Sornsrivichai, J., Kawano, S., 2004. Prediction of ripe-stage eating quality of mango fruit from its harvest quality measured nondestructively by near infrared spectroscopy. Postharvest Biol. Technol. 31 (2), 137–145.
Saure, M.C., 1996. Reassessment of the role of calcium in development of bitter pit in apple. Funct. Plant Biol. 23 (3), 237–243.
Simon, E.W., 1978. The symptoms of calcium deficiency in plants. New Phytol. 80, 1–15.
Slaughter, D.C., 1995. Nondestructive determination of internal quality in peaches and nectarines. Trans. ASAE 38 (2), 617–623.
Upchurch, B.L., Affeldt, H.A., Hruschka, W.R., Norris, K.H., Throop, J.A., 1990. Spectrophotometric study of bruises on whole, 'Red Delicious' apples. Trans. ASABE 33 (2), 585–589.
Williams, P., Norris, K.H., 2001. Variable affecting near infrared spectroscopic analysis, In: Williams, P., Norris, K.H. (Eds.), Near Infrared Technology in the Agriculture and Food Industries. 2nd ed. The American Association of Cereal Chemists, St. Paul, MN, pp. 171–185.
Wills, R.B.H., Scott, K.J., Lyford, P.B., Smale, P.E., 1976. Prediction of bitter pit with calcium content of apple fruit. N. Z. J. Agric. Res. 19 (4), 513–519.
Wooldridge, J., 1999. Bitter pit in apples: effect of physical and chemical soil factors. Dec. Fr. Gr. Feb s7–s10.
Woolley, J.T., 1971. Reflectance and transmittance of light by leaves. Plant Physiol. 47, 656–662.
Xing, J., De Baerdemaeker, J., 2007. Fresh bruise detection by predicting softening index of apple tissue using VIS/NIR spectroscopy. Postharvest Biol. Technol. 45 (2), 176–183.
Xing, J., Bravo, C., Moshou, D., Ramon, H., De Baerdemaeker, J., 2006. Bruise detection on 'Golden Delicious' apples by VIS/NIR spectroscopy. Comput. Electron. Agric. 52 (1), 11–20.
Zhang, S., Zhang, H., Zhao, Y., Guo, W., Zhao, H., 2013. A simple identification model for subtle bruises on the fresh jujube based on NIR spectroscopy. Math. Comput. Model. 58 (3), 545–550.