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ORIGINAL ARTICLE

Non-invasive hyperspectral imaging approach for fruit quality control application and classification: case study of apple, chikoo, guava fruits

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Abstract Mechanical injuries to fruits are often caused due to hidden internal damages that results in bruising of fruit. This is a serious cause of concern to the fruit industry, as spoiled or bruised fruits directly impact the producers profit. Hyperspectral imaging method can provide the ability to identify these internal bruises to classify these fruits as normal and injured (bruised), reducing time and increasing efficiency over the sorting line in marketing chain. In this paper, we have used three types of fruits i.e., apple, chikoo & guava for experiments. The mechanical injury is introduced by manual impact on surface of the fruits sample and hyperspectral images were captured over nine narrow band pass filters to produce hyperspectral cubes for a fruit. Three types of methods were used for the data processing. First two are non-invasive in nature i.e., pixel signatures over hyperspectral cubes and second is prediction model for classification of fruits quality into normal and bruised using feed forward back propagation neural network. Finally, invasive method is used to confirm the said prediction model using parameters like firmness, Total Soluble Solid (TSS) and weight with Principal Component Analysis. Results obtained by hyperspectral imaging method indicate scope for non-invasive quality control over spectral wavelength range of 400–1000 nm.

Keywords Hyperspectral imaging · Grey Level Co-occurrence Matrix (GLCM) · Feed forward-back propagation network · Principal Component Analysis (PCA)

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Introduction

Mechanical damage in fruits causes internal tissue damage which is in turn called as ‘Fruits internal bruising’, that result in development of entry points for fungus and bacteria, increased water loss, that can have a great impact on the fruits quality and nutrition profile of the fruits, causing significant economic losses to fruit processing industry and the retailer, thereby lowering the quality grade of the fruits (Dixie 2005). Bruising is one of the major surface defects in fruits. It results when chemical compounds present in the fruits are oxidized i.e., when the skin of the fruit, walls and membranes of the cells within the fruit is ruptured. These compounds then react with oxygen, usually incorporating it into their molecular structure, resulting into the browning of the tissue, which is the sign of bruising. Various chemical reactions begin when the fruit cellular structures are broken. The vacuoles inside the cells containing a type of chemical called phenols are broken and an enzyme called polyphenol oxidase or tryosinase causes damaged fruits to turn brown. This color change is due to the aerobic oxidation of phenols to quinines, which continue to react with each other forming a brown pigment called melanin. Ripen fruits are vulnerable to mechanical stress leading to injury to tissues causing bruising. This is because the consequence of cell walls and turgor changes causes internal tissue to become less elastic and more plastic. This leads to weaker tissue structure with ripening. Bruising is the reason for rejecting the highest number of fruits in sorting lines, wherein manual vision based commercial defect sorting systems have poor capability for detecting subtle defects like bruises (Lu 2003; Kleynen et al. 2005). Superiority and safety are the key factors in modern fruit processing industries, which is not possible using currently available conventional invasive measurement methods like firmess measurement (which use Penetrometer instrument) and Total Soluble Solid(TSS). Penetrometer is used to determine the fruit maturity and ripeness while Refractometer measures primary soluble solids such as Sugar, Sucrose, Fructose and Glucose. There are other invasive method i.e., chemical analysis which measures nutrients contents like carbohydrates, fats, proteins, pH etc. So these invasive fruit quality measurement systems are destructive and inefficient, therefore development of non-destructive, non-invasive and efficient measurement of quality is mandatory. Recently, optical sensing technologies have been investigated as potential tools for non-destructive evaluation and inspection of fruit superiority and safety. In particular, hyperspectral imaging or imaging spectroscopy (Sun 2010), which is based on two mature technologies of imaging (Sun 2008a) and spectroscopy (Sun 2008b), have been widely studied recently to developed many successful quality control applications in the industry.

Hyperspectral imaging is a dominant technique which acquires high quality spatial and spectral information over a continuous electromagnetic spectrum. The robust, reliable combination of chemical (molecular spectroscopy) and physical (digital imaging) features have been successfully applied in a variety of fields such as remote sensing(Kokaly et al. 2009; Sabins 1999), astronomy (Gao et al. 2009; Verrelst et al. 2010), agriculture (Vigneau et al. 2011; Sommer et al. 1998), food (Gowen et al. 2007) and pharmaceuticals industries (Gendrin et al. 2007; Ravn et al. 2008). When a fruit is exposed to light, good amount of the incident light is reflected at the outer surface, causing specular reflectance, and the remaining incident energy is transmitted through the surface into the cellular structure of the fruit where it is scattered back by the small interfaces within the tissue or absorbed by cellular constituents (Fig. 1a) (Birth 1976). The reflected and re-scattered radiation can be measured and recorded as an absorption/reflectance spectrum (Bochereau et al. 1992). This type of imaging spectroscopy helps in characterizing physical materials using the principle of the varying absorption or emission at different wavelengths of spectrum.

Elmasry et al. (2007) developed a calliberation model to predict quality attributes of Strawberry like moisture content, TSS and 'pH' using Multiple Linear Regression (MLR) and identifying ripening stages by using texture analysis method called grey-level co-occurrence matrix (GLCM). Baranowski et al. (2012) used PCA and Minimum Noise Fraction (MNF) analysis to distinguish between areas with defected tissue for early bruises detection in apple with varying depths using hyperspectral and thermal imaging in the broad spectrum range (400–5000 nm). Li et al. (2011) detected defects in orange by evaluating hyperspectral images of samples using PCA in on-line imaging system in the spectral range (400–1000 nm). Most of the above studies mainly deals with developing prediction model to determine fruit quality attributes such as firmness, 'pH', moisture, TSS etc. and internal bruises of a particular type of fruit. As far as literature survey is concerned there are no studies till date for the classification of normal and injured (bruised) fruits like guava and chikoo. The fruits like; Guava and chikoo which are actually the storehouse of various nutrients profile are equally essential in day today life. These fruits are rich in dietary fiber, antioxidant, vitamins and potassium. GLCM (Haralick et al. 1973) is a textural feature extraction method which provides contrast, correlation, energy and homogenity of the object. This type of method can play major role in imaging technology which provides texture information. Here in our study's we have demonstrated the GLCM approach for bruise analysis over time. The signature analysis indicates the progression of bruises, the GLCM approach also classify the normal and bruised fruits. Further the same is verified using invasive studies. The best part of this paper is that simultaneously three fruits (having diverse skin structures) were studied and common methodologies of classification were established for bruises detection. This research gives insight for extending the work for quantification of bruises level.

The main objective of this research is to study the use of hyperspectral imaging in the spectral region of 400–1000 nm for classification of normal and injured (bruised) fruits for three different types i.e., apple, chikoo, guava. Specific objectives are categorized below.

a. Non-Invasive studies

   i. develop a visible and near infrared regions (400–1000 nm) hyperspectral imaging system for acquisition of reflectance mode images.
   ii. extraction of texture information of fruit images using GLCM.
   iii. classify fruits for normal and injured (bruised) with feed forward back propagation prediction neural network model using texture feature extracted from GLCM.

b. Invasive studies

   i. Establishing TSS, firmness, weight parameters for fruits.
   ii. Data classification studies through Principle Component Analysis.

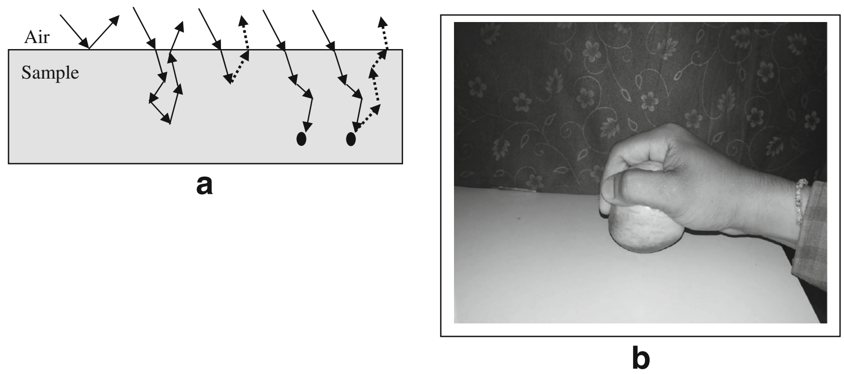

Fig. 1 **a**. Interection of white light with sample and Scattering phenomenon; **b**. Method of introducing mechanical injury

Materials and methods

Fruit samples and injury development

Here in this study we selected, total 90 number fruits, (30 numbers of each fruits (red delicious apples, chikoo, guava)) were purchased from the local Panaji fruit market, Goa, India. Red delicious apple belongs to rose family and it is scientifically called as Malus domestica. Chikoo is the domestic name and scientifically known as Manilkara zapota, commonly known as the sapodilla. Guava are commonly tropical fruits, we used Green apple guavas and scientifically known as Psidium Quajava and belong to myrtle family. These fruits were confirmed for experimentation with expert opinion from Indian Council of Agriculture Research (ICAR), Goa, India. Almost all the purchased fruits were equally ripened and bruises free. The weight of fruit i.e., for apple (130–140 g), chikoo (60–70 g) and guava (130–140 g) were chosen randomly. Here region of interest (ROI) were marked with the marker pen and cleaned with wet tissue paper to wipe out wax if any. These ROI was then subjected to localized injury.

There are various ways in which mechanical injury to fruits can be introduced. Some of the mechanical injury introduces by the researcher in the past includes plastic roller dropping, dropping on flat steel plate, impact of a pendulum and rolling under load to simulate stress (Baranowski et al. 2012). We here introduced bruises through mechanical impact method manually by hand as shown in Fig. 1b. The impact can be introduced by selective torque adjustment method or through impact of pendulum which are reproducible. The use of mechanical impact to introduce internal artificial injury is similar to injury developed to fruits during marketing chain. Some of these includes reckless handling by pickers to empty fruits from picking bags to bulk bins; transportation of fruits over bumpy and rough surface in bin tractor and trailer; the forklift operator lowering too fast and comes to a halt with a bump, etc. Here, in this study we were more interested in invasive and non-invasive analysis for three fruits rather than the quantification of bruises which eliminates the concern of depth of injury. Thus initially all '30'fruits corresponding to each type were separated into two categories of '15' each. Out of these six groups of categories, we labeled them as *Class* App_G*, Class* App_{In}*, Class* $Chik_G$*, Class* $Chik_{In}$*, Class* $Guava_G$ *and Class* $Guava_{In}$. The suffix 'G' stands for good or normal fruit and 'In' stands for injured or bruised fruit. Here 'App' stands for Apple, 'Chik' stands for Chikoo and 'Guava' stands for Guava. From these six groups, normal fruits groups were recorded for hyperspectral images and subsequently subjected to invasive studies for TSS and firmness. Other injured three groups after manual bruises were kept aside in dry storage media for hyperspectral imaging. Then over 24 h of period for consecutive 3 days hyperspectral images were captured for the injured fruits. Later, on the fifth day of experiment, invasive studies were performed for TSS and firmness measurements were performed.

Hyperspectral imaging system

A hyperspectral imaging system was setup in dark room at Department of Electronics, Goa University, Taleigao Plateau, Goa, India, as shown in Fig. 2a and b. It consist of illumination unit design in-house for 250 W output power of Quartz Tungsten Halogen (QTH) lamps having specification similar to Newport 6336 model, adjusted at angle of 45°, 45 cm from the platform of fruit with an adjustable light focusing beam to illuminate the camera's field of view, over fruit holder to provide uniform lighting conditions. The hyperspectral images are captured using C-cam Technology, Vector International, Leuven, Belgium, BCi5-U-M-40-LP camera having CMOS sensor with spectral range (400 to 1000 nm). Most of the researcher have used CCD camera. The advantage of use of CMOS over CCD is it high speed, low cost, low power consumption and small size. Usually, CCD sensors create high quality images with low noise (grain). CMOS images tend to be higher in noise. CCD sensors are more sensitive to light. CMOS sensors need more light to create a low noise image at proper exposure. Hence we have use variable power light source with variable integration time. Camera with sensor area of 1280 × 1024 pixels having a Multi-Slope Exposure mode, that prevents over-

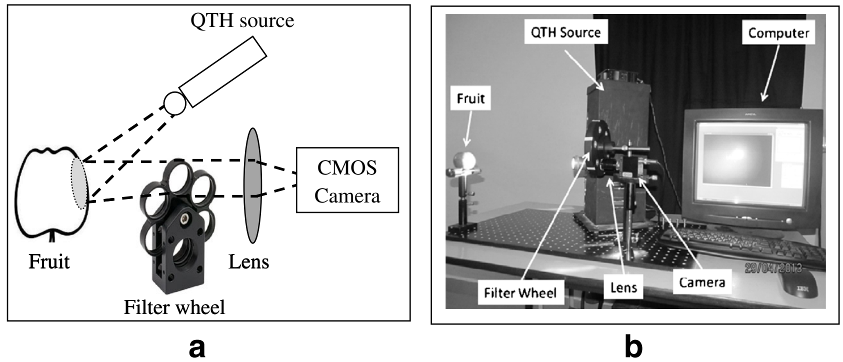

Fig. 2 Hyperspectral Imaging setup

exposure of brighter parts of an image while preserving excellent contrast in the darker areas of the image. The Pixel pitch of the camera is 6.7 × 6.7 μm for the active image area of 8.58 mm (H) × 6.86 mm (V). Estimated spatial resolution was 200 pixel /cm. The sensor has a remarkably good signal-to-noise ratio in combination with excellent contrast performance and a compatible near infra-red lens (Apo-Xenoplan 2.8/50) from Schneider Optics having transmission range (400 to 1000 nm) with F-number 2.8 and focal length of 50.2 mm. Various narrow band filters (from CVI Laser Optics, F-Bandpass Interference filters) have been used within experimental range such as 530 nm, 590 nm, 650 nm, 710 nm, 770 nm, 830 nm, 890 nm, 950 nm, 1000 nm in order to generate hyperspectral images in said spectral range. Here, during capturing of images, care has to be taken to avoid the multiple reflections in the room by maintaining constant position of the operators wearing white bonny suits for same ambient conditions. All these filters were attached to a filter wheel to facilitate faster image capturing. The time taken to capture hyperspectral images for one single fruit was 1 min due to the manual handling of the system. The use of these interference filters has excellent advantage over Acoustic-Optic Tunable Filters (AOTFs) and Liquid Crystal Tunable Filters (LCTFs) used by the most of the researchers due to their small size, low cost, light weight, speed of wavelength tuning and high optical throughput which becomes an better option as compared to tunable filters (Edelman et al. 2012).

Hyperspectral images database generation

Hyperspectral images were acquired initially on the first day for normal fruit class i.e., *Class* X_G where *'X'* is fruit type, to capture total 405 images. Further, injured fruit class i.e., *Class* X_{In} were recorded for Hyperspectral images for same sets of filters after 24 h of period over 3 days. Hence total 405 hyperspectral images were obtained for each day. Hence total 405 × 3 = 1215 images were obtained for injured fruits and 405 for normal fruits were generated in database as partially shown in Fig. 3.

Data processing and analyses

Multispectral images captured over spectral bands interference filters for normal and injured fruits were cropped for ROI for pixel size of 500 × 500, 400 × 600, 300 × 450 for apple, chikoo, guava respectively inside manually marked ROI. These images were pre-processed with third order interpolation (Eq.1) method across nine spectral bands as mentioned earlier to generate pixel signatures of total number 250,000, 240,000, 135,000 spectral signature for apple, chikoo and guava respectively generating virtual hyperspectral signatures. These signatures were averaged for every image to reduce the random noise associated during the data recording. Such an averaging also eliminates the pixel alignment error during changeover of filter for next band. Further, the spectral signatures were averaged at second level for a group for every day to produce signature for a day, which guarantee that inter-fruit random measurement errors are nullified in a class.

$$y[n] = x[n] + \frac{x[n-1] + x[n+2]}{3} + \frac{2(x[n-2] + x[n+1])}{3} \quad (1)$$

Where *'y[n]'* represents interpolated point of five *'x[n], x[n+1], x[n+2], x[n-1], x[n-2]'* sample points; to generate virtual hyperspectral data.

Hence, the final spectral signature obtained were free from random ambient noise during experimental recording.

As hyperspectral data cube contains data across a range of contiguous spectral bands, having significant volume of highly correlated data, especially in adjacent bands. Processing this high volume of data is computationally expensive. Therefore, it is essential to extract uncorrelated components as features from this highly correlated data for purpose of efficiency and effectiveness. The characteristic features were extracted by examining texture of fruits over each spectral band images i.e., across the individual slice of spectral cube with the help of GLCM, also known as the gray-level spatial dependence matrix. The GLCM functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image,

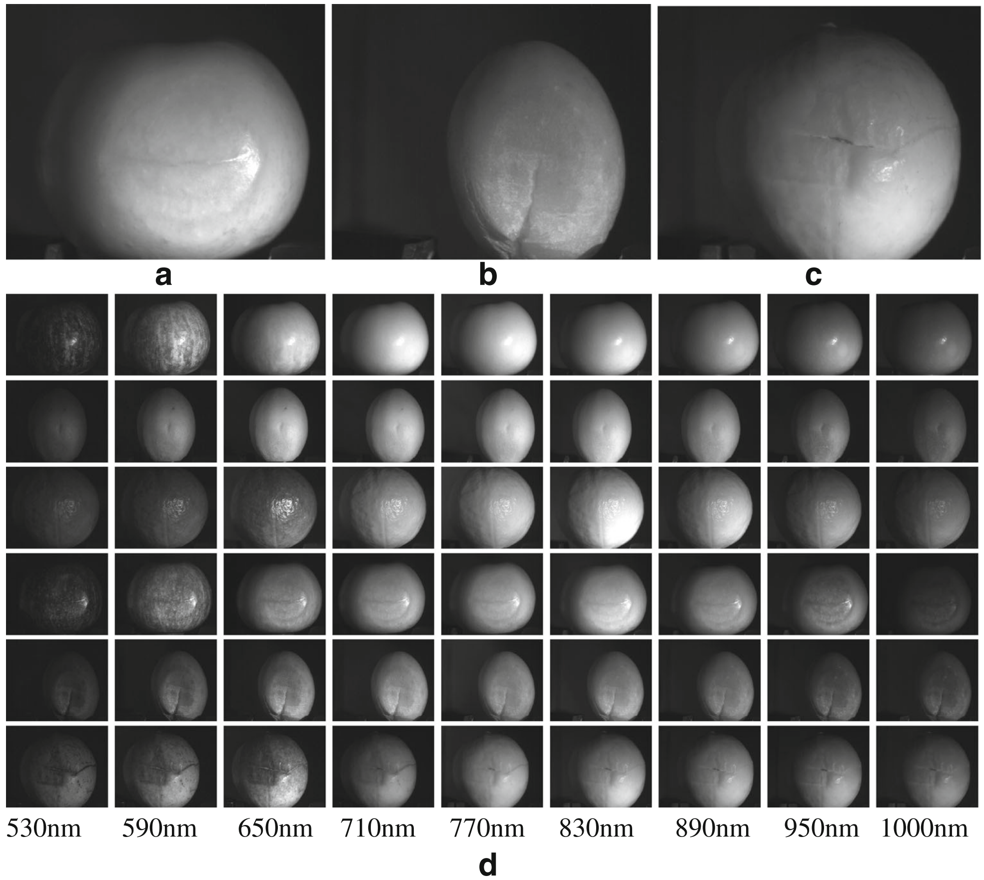

Fig. 3 **a**. Fruit apple image at 830 nm; **b**. Fruit chikoo image at 830 nm; **c**. Fruit guava at 830 nm; **d**. First three rows represent Hyperspectral imaging of normal fruit like apple, chikoo, guava respectively. Last three rows represent Hyperspectral database for the injured fruit like apple, chikoo, guava respectively

creating a GLCM, and then extracting statistical measures from this matrix. Generally, texture analysis characterizes regions in an image by their texture content in terms of smoothness, roughness, silkiness, or bumpiness in the context of an image. In this case, these characteristics refer to variations in the brightness values, or grey levels. A co-occurrence matrix is a square matrix with elements corresponding to the relative frequency 'P_{ij}' of occurrence of pairs of grey level of pixels separated by a certain distance 'D' in a given direction (0°, 45°, 90°, or 135°) as shown in Fig. 4a. Each entry (i, j) in GLCM corresponds to the number of occurrences of the pair of grey levels 'i' and 'j' which are a distance 'D' apart in the image. The following GLCM parameters were calculated in MATLAB 7.10.0 (R2010a) to express texture:

- **Contrast** measure the intensity between a pixel and its neighbor over the whole image in GLCM.

$$Contrast = \sum_{i,j=0}^{N-1} P_{ij}(i-j)^2 \quad (2)$$

- **Correlation** is the measure of how correlated a pixel is to its neighbor over the whole image in GLCM.

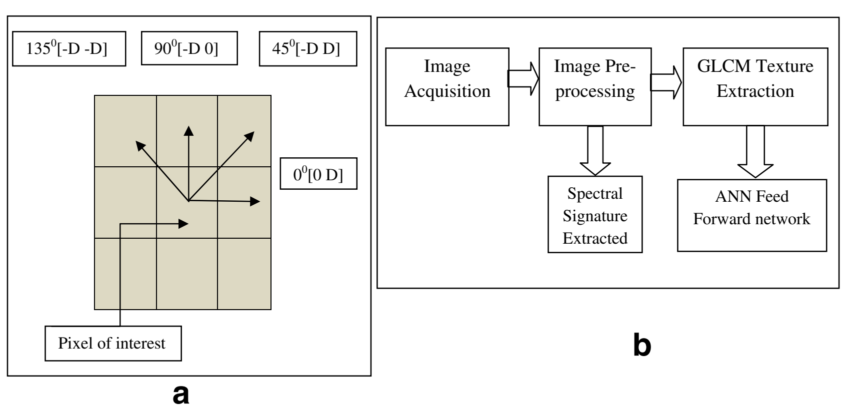

Fig. 4 **a**. Extraction of GLCM at different directions (0°, 45°, 90°, and 135°); **b**. Block diagram of classification of fruit for normal and bruised using ANN

$$Correlation = \sum_{i,j=0}^{N-1} P_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2} \quad (3)$$

- **Energy** provides the sum of squared elements in the GLCM. Also known as uniformity or the angular second moment.

$$Energy = \sum_{i,j=0}^{N-1} P_{ij}{}^2 \quad (4)$$

- **Homogeneity** measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

$$Homogeneity = \sum_{i,j=0}^{N-1} \frac{P_{ij}}{1+(i-j)^2} \quad (5)$$

Where, N=Number of gray levels in the image, the 'μ' and 'σ' are mean and standard deviation respectively. The cell walls of fruits are mainly composed of polysaccharides including pectin. During ripening these pectin's are converted from a water insoluble form to water soluble form by breakdown of enzyme called polygalacturonase. The fruit becomes less firm as the structure of fruit is degraded and thus the hydrolysis of storage polysaccharides occurred during ripening. The use of GLCM has been shown by Elmasry et al. (2007) for identifying ripeness stage of strawberry based on texture analysis. Bruising is also similar process to ripening where changes occurs in tissue structures due to the chemical processes within the fruit. The obtained texture parameters from GLCM becomes then applied as a input to the feed forward back propagation neural network. We computed GLCM vectors for two directions i.e., 0° and 90°; for every fruit over each spectral band by rotating the image by 90° due to the variable special relationships of pixels in other directions and distance. For every spectral band having 256 gray level in an image, two GLCM features vector (2×4=8) having four parameters i.e., contrast, correlation, energy and homogeneity were computed.

Artificial neural networks (ANN) have proven to be very effective in identification and classification (Bochereau et al. 1992; Jayas et al. 2000), where non-coherence or non-linearity often exists. ANN appeared to be well suited method for classification of fruit grown or stored under different conditions (Elmasry et al. 2009).

The feed forward back propagation network was simplest type of artificial neural network mainly designed for pattern classification in the data. In this network, the information moves in only one direction i.e., forward; from the input nodes, through the hidden nodes (if any) and to the output nodes. There are no cycles or loops in the network. Here, ANN model has used feed forward back propagation network with eight input nodes, two output nodes and two hidden layers. Therefore, the texture information obtained as shown in Fig. 4b has been feed as the input to the network and the network was trained till the paramount universal weights in the hidden layers were obtained to give optimum performance for classifying normal and injured (bruised) fruits.

Invasive technique for fruit quality

Similar study for classifying fruit quality for normal and injured (bruised) were performed for quality attributes such as firmness, total soluble solids (TSS) and weights using invasive destructive method. Here on first day of experiment as mentioned earlier, 15 fruits from each group of normal fruits i.e., Class App_G, Class $Chik_G$ and Class $Guava_G$ were subjected for TSS and firmness studies. Subsequently after 4 days of bruising development, other remaining three groups i.e., Class App_{In}, Class $Chik_{In}$ and Class $Guava_{In;}$ were subjected to TSS and firmness studies at ICAR laboratory. For each fruit sample, total 11 readings (five firmness, five TSS and one weight) were obtained to reduce the human error. Thus for each group of fruit including normal and injured (bruised) fruit, total 990 readings were obtained.

The data obtained was then analyzed using Principle Component Analysis (PCA) with the help of XLSTAT 2013.6.04 software (http://www.xlstat.com) for the classification of normal and bruised fruits. The PCA transforms the acquired data set into a new coordinate system with the greatest variance of the data set projected in the first coordinate (also called the first principal component) and the second greatest variance on the second coordinate and so on in multi-dimensions eigen space. The PCA is mainly used in dimensional reduction of the acquired data set while retaining the important characteristic, which contributes most of the variance.

Result and discussion

Spectral signature analysis

The spectral signature pre-processed over third order interpolation method as mentioned above and as shown in Fig. 5 indicates reflectance spectra's obtained over spectral band of 400–1000 nm. These reflectance spectra's shows higher reflectance on the day one when the fruits were fresh. This is because as internal structure was not damaged or injured and hence tissues of fruits were intact showing high reflectance spectra. As the mechanical injury was introduced, there was decrease in the reflectance spectra of fruits as shown in Fig. 5 for second day. This decrease in reflectance spectra may be due to the changes occur during ripening that results in change in color, firmness and moisture content; various enzymatic

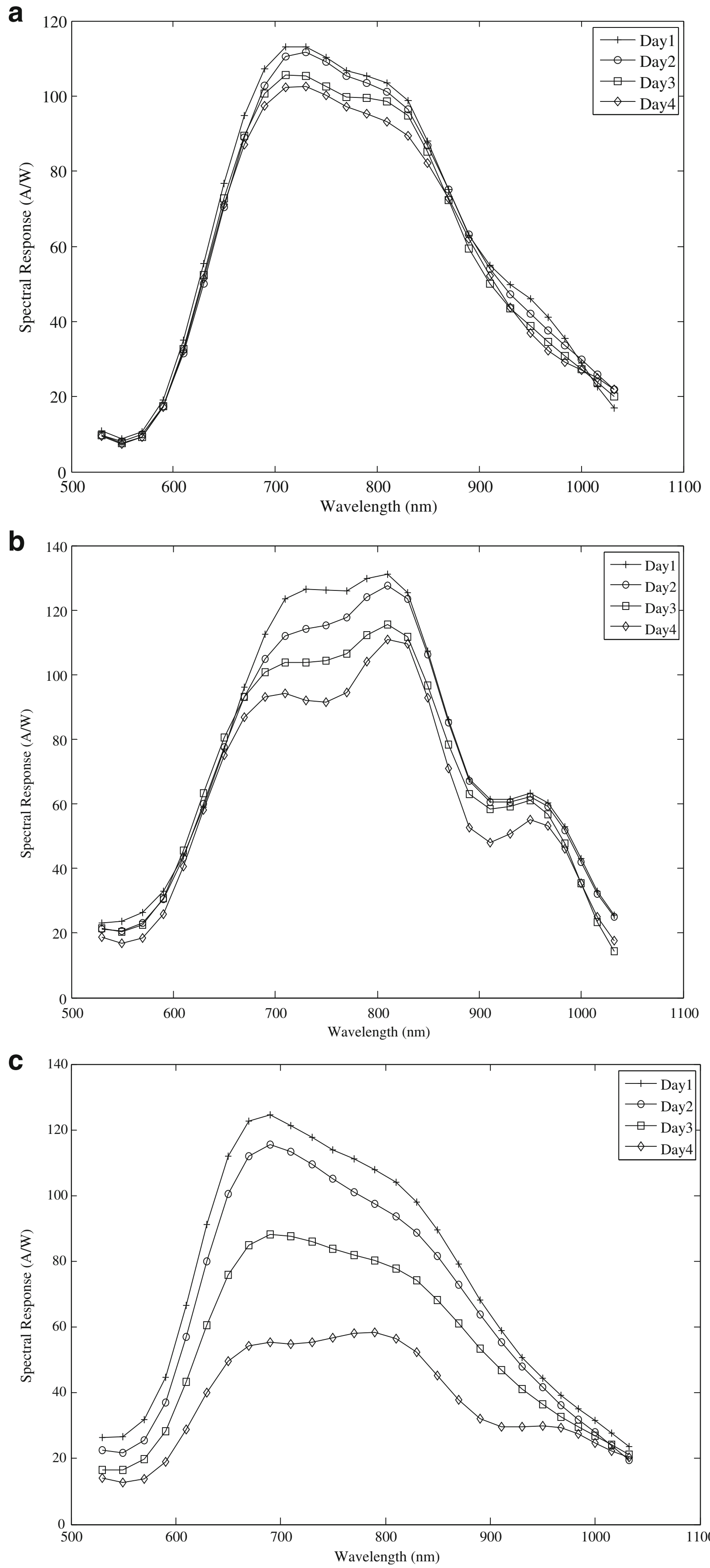

Fig. 5 Reflectance spectral signature of **a**. apple; **b**. chikoo; **c**. guava

reactions during mechanical injury to fruits when tissues come in contact with oxygen in the air or rupture of tissue internally, results in change in color (most of the fruit color after bruising is brown in color) and scattering co-efficients. Similarly, more significant separation were observed in the spectral signature of all three fruits for remaining 2 days, as the experiment was conducted for 4 days over the time span of 24 h. As far as spectral signature of individual fruit is concerned, apple shows distinct classification results in the spectral range of 650–850 nm, chikoo in the spectral range of 700–900 nm and guava in the spectral range of 550–950 nm. These spectral signature response indicate the candidature for the classification between normal and injured (bruised) fruits. Similar such studies are confirmed by researchers like Mendosa et al. (2011), Rajkumar et al. (2012), Li et al. (2011) for apple, banana and orange respectively. Our approach in this paper represents the spectral response of normal and injured (bruised) portion of fruit obtained from Hyperspectral Imaging profile. The most of the researchers have worked on fruits like apple, banana, cucumber, orange, grapes etc.

Non-invasive classification of fruits for normal and injured: an ANN approach

The texture information vectors obtained from the GLCM method were introduced at the input nodes of feed forward back propagation network as defined earlier using neural network (Matlab 7.10.0 (R2010a)) toolbox. The network was trained to classify the particular type of fruit for normal and injured (bruised) and two output pattern [1,0] and [0,1] respectivley were obtained at the output of the network.

Here in this modeling out of 100 % (15×9+15×9×3=540) images of the total database, 60 % (324) images were kept for training, 20 % (108) images were for validation and 20 % (108) images were for testing and the test result in the form of confusion matrix were obtained as indicated in the Table 1 for apple chikoo, guava. The result obtained in confusion matrix shows promising approach for classification of fruit quality which play a vital role in the sorting line when handling quality control in fruit processing industry. As seen from the result for correct classification an average value of 83.3 % for three fruits using feed forward back propagation network: apple (79.5 % correctly classification, 20.5 % false classification), chikoo (84.1 % correctly classification, 15.9 % false classification), guava (86.4 % correctly classification, 13.6 % false classification), indicates the second candidature for classification approach for normal and injured fruits. The false classification average value is 16.7 %. This may be due to the fact that the database was obtained for 3 days after the injury and since the progression of injury is slow in fruits it becomes difficult to extract the signatures of injury on first 2 days. This false classification can be improved by considering normal fruits on the first day and injured fruits on third day. ANN back propagation approach has been successfully utilized in food quality control to relate the average spectra obtained from selected trees to estimate citrus yield of individual tree by Ye et al. (2006). Also, Plaza et al. (2004) characterized mixed pixels in remotely sensed hyperspectral images using neural network.

Invasive classification of fruits for normal and injured: PCA approach

The confirmation of results obtained from neural network in the form of confusion matrix was then verified with the destructive method (Invasive method) for parameters like firmness, TSS and weight (Fig. 6). These parameters were processed for component analysis for classification using PCA algorithm and outstanding results were obtained. As shown in Fig. 7, the classification result based on first principle component (F1) and second principle component (F2) showing distinct clustering for normal and injured fruits. The results were obtained for 'F1' and 'F2' corresponding to total contribution of 89.11, 95.02, 94.6 %. Similar studies for classification of data have been performed by various researchers using PCA. Williams et al. (2012) used this approach to monitor chemical changes associated with fungal activity in maize, Wang et al. (2012) have shown the classification for healthy and sour skin in an infected onion, Gowen et al. (2009) adopted to classify whole mushrooms into undamaged and freeze-damaged groups and Kamruzzaman et al. (2012) used PCA for categorizing red meat species.

Table 1 Confusion matrix of apple, chikoo, guava

	Confusion matrix of apple			Confusion matrix of chikoo			Confusion matrix of guava		
Output class	59 %	6.8 %	89.7 % 10.3 %	70.5 %	13.6 %	83.8 % 16.2 %	68.2 %	9.1 %	88.2 % 11.8 %
	13 %	20.5 %	60.0 % 40.0 %	2.3 %	13.6 %	85.7 % 14.3 %	4.5 %	18.2 %	80.0 % 20.0 %
	81.3 %	75.0 %	79.5 %	96.9 %	50.0 %	84.1 %	93.8 %	66.7 %	86.4 %
	18.8 %	25.0 %	20.5 %	3.1 %	50.0 %	15.9 %	6.3 %	33.3 %	13.6 %
	Target class								

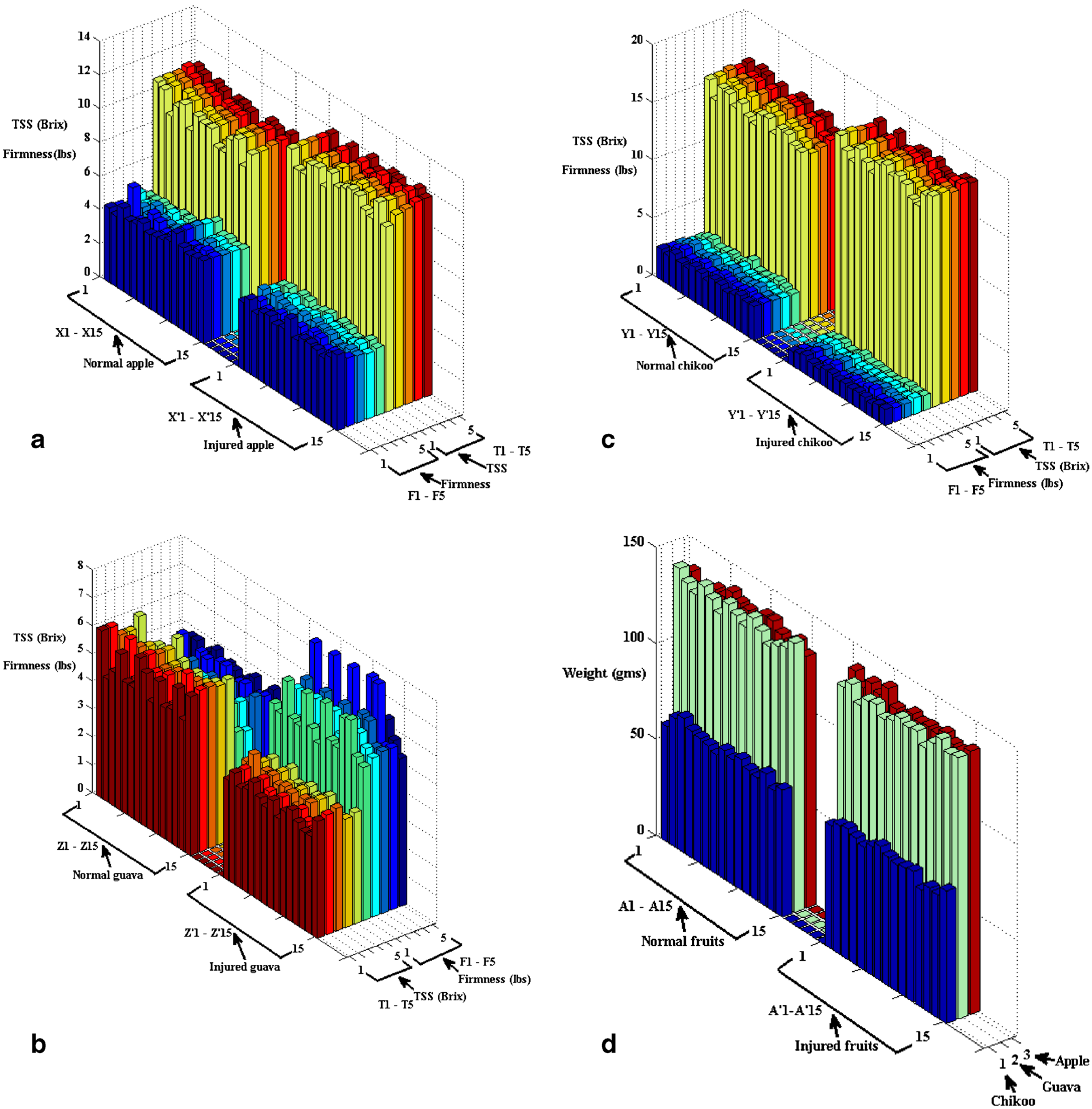

Fig. 6 **a**. Firmness and TSS parameter of 15 normal and 15 injured apple; **b**. Firmness and TSS parameter of 15 normal and 15 injured guava; **c**. Firmness and TSS parameter of 15 normal and 15 injured chikoo; **d**. Weight of 15 normal and 15 injured apple, guava, chikoo

This work can be extended for quantifying the level of bruises. Also, one can establish studies of internal defects as performed by Ariana and Lu (2010). Ariana et al. carried out study to select important wavebands to speed up the detection of internal defects in pickling cucumbers and whole pickles in an online inspection system. One can also develop the prediction model for the various parameters using PLS. Such types of models are developed by several researches. Rajkumar et al. (2012) studied banana fruit quality parameters like moisture content, firmness and TSS and maturity at three different temperature 20, 25 and 30 °C in vis/NIR (400–1000 nm) spectral range. These quality parameters were anlaysed for prediction model using Partial Least Square(PLS) analysis. Mendosa et al.(2011) developed improved firmness and soluble solid content (SSC) prediction model using PLS method for ‘Golden Delicious’ (GD), ‘Jonagold’ (JG), and ‘Red Delicious’ (RD) apples by integrating spectral

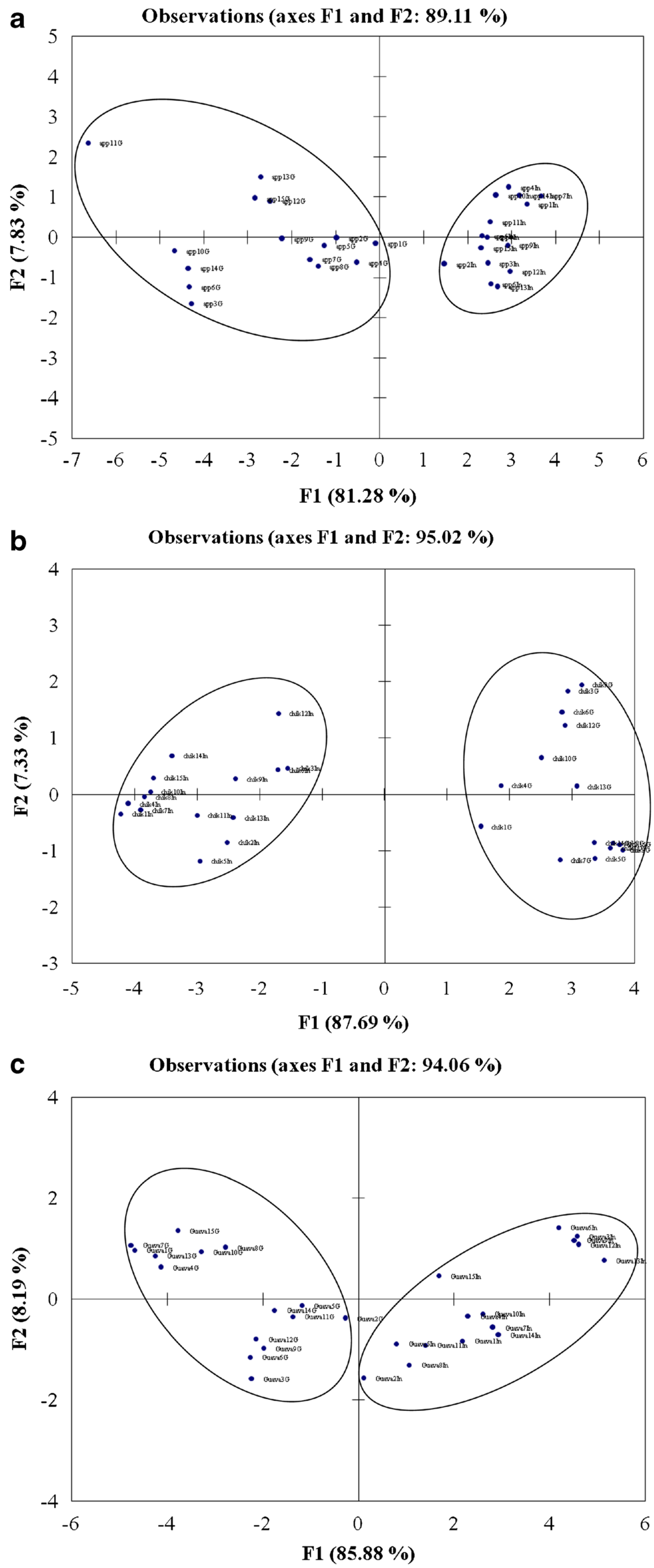

Fig. 7 Classification fruit for normal and injured using PCA **a**. Apple **b**. Chikoo, **c**. Guava

and image features extracted over 500–1000 nm wavelength region. Leiva-Valenzuela et al. (2013) introduced a pushbroom hyperspectral imaging for blueberries at stem and calyx ends for predicting the firmness and SSC in the spectra region of 500–1000 nm and developed prediction model to estimate quality parameters using PLS method. Fernandes et al. (2011) used adaptive boosting neural network for estimating concentration of grape anthocyanin in the wavelenght range 400–1000 nm, wherein input pattern for neural network is obtained by extracting features by Principle Component Analysis (PCA) algorithm. Hence, such model can be used for quantitative and qualitative accessments of the nutrients in marketing chains of food processing.

Conclusion

Hyperspectral images have been captured for fruits i.e., apple, chikoo, guava (normal and injured) using CMOS camera for nine filter spectral bands in the range 400–1000 nm. The spectral reflectance obtained for hyperspectral cube of fruit were interpolated over spectral bands, for hyperspectral cube showing the classification in the spectral response for normal and injured (bruised) fruits. These spectral signatures indicate distinct variation of the signatures in far visible and NIR region over time period. Apple shows distinct classification for normal and injured fruit over a 4 days of hyperspectral imaging in the spectral range of 650–850 nm, chikoo in the spectral range of 700–900 nm and guava in the spectral range of 550–950 nm. Further bruising developed due to physical injury obtained using GLCM feature extraction based neural network algorithm shows satisfactory results obtained in the form of confusion matrix. GLCM which is satisfactorily applied previously in studying the ripening stages (Elmasry et al. 2007) in fruits has been extended for bruising in this study. Both the processes i.e., ripening and bruising are almost similar in line with reference to chemical process in the internal cell walls of the tissue due to enzymatic reactions. The results found by non-invasive method are then verified with invasive approach for parameters like TSS, firmness and weight using PCA. The proposed method can be extended for quantification of the bruises which will have high potential in providing quality control in Industries using non-invasive hyperspectral imaging.

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