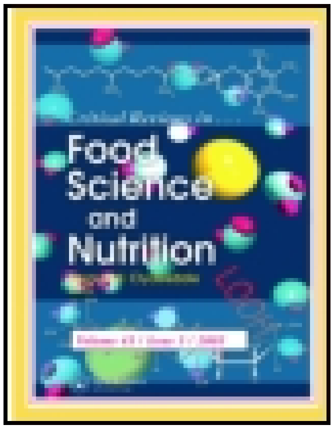

Critical Reviews in Food Science and Nutrition
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/bfsn20

Recent developments and applications of hyperspectral imaging for quality evaluation of agricultural products: a review

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Accepted author version posted online: 02 Jul 2013.

To cite this article: Dan Liu, Xin-An Zeng & Da-Wen Sun (2013): Recent developments and applications of hyperspectral imaging for quality evaluation of agricultural products: a review, Critical Reviews in Food Science and Nutrition, DOI: 10.1080/10408398.2013.777020

To link to this article: http://dx.doi.org/10.1080/10408398.2013.777020

Recent developments and applications of hyperspectral imaging for quality evaluation of agricultural products: a review

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Abstract

Food quality and safety is the foremost issue for consumers, retailers as well as regulatory authorities. Most quality parameters are assessed by traditional methods, which are time consuming, laborious and associated with inconsistency and variability. Non-destructive methods have been developed to objectively measure quality attributes for various kinds of food. In recent years, hyperspectral imaging (HSI) has matured into one of the most powerful tools for quality evaluation of agricultural and food products. Hyperspectral imaging allows characterization of a sample's chemical composition (spectroscopic component) and external features (imaging component) in each point of the image with full spectral information. In order to track the latest

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research developments of this technology, this paper gives a detailed overview of the theory and fundamentals behind this technology and discusses its applications in the field of quality evaluation of agricultural products. Additionally, future potentials of hyperspectral imaging are also reported.

Keywords: non-destructive methods, hyperspectral imaging, computer vision, NIR, chemometrics, data mining, food quality.

INTRODUCTION

Food quality and safety problems are frequently confronted in our daily life, so there has been an increasing focus from the consumers on the quality and safety of foods that they consumed. Presently analytical methods available for quality evaluation are mostly slow and destructive. Therefore, it is urgent to develop non-invasive, efficient and quick testing method for monitoring food quality. New non-destructive techniques, especially based on optical properties (Nicolaï et al., 2007) and visual evaluation (Sun, 2009) are being carried out worldwide for testing various kinds of food. Spectroscopy has proven to be an outstanding tool for analysis of agricultural and food products due to its fast measurement, with little or no tedious sample preparation, good adaptability and simultaneous determination of different attributes. Visible and near infrared

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(Vis-NIR) spectroscopy is one of the powerful spectroscopic tools for food quality evaluation. The method is based on measurement of spectral characteristics change of the sample irradiated with electromagnetic radiation over a waveband 400-700 nm for visible region and 700-2500 nm for near-infrared region. The spectral characteristics recorded in reflection, transmission and transflection modes depend on structural and biochemical components of the product as well as its light scattering properties. The absorption signatures of samples are related to molecular overtones and combinations of these fundamental vibrations due to the stretching and bending of N-H, O-H and C-H groups in the NIR region and electronic transitions of visible portions of the electromagnetic spectrum. Vis-NIR spectroscopy was first used in agricultural applications by Norris (1964) to measure moisture in grain. Since then it has a wide application for rapid analysis of chemical and structural composition of many agricultural and food products. For instance, it can be used for measuring water content of mushrooms (Roy et al., 1993), firmness, soluble-solids of kiwifruit (McGlone et al., 1998), and internal damage of apples (Clark et al., 2003). NIR spectroscopy also offers many possibilities for identification and classification of the food constituent such as discrimination of commercial white wine (Cozzolino et al., 2003) or olive oil (Kasemsumran et al., 2005). Despite its wide applications, the molecular overtone and combination bands in NIR are typically very broad and frequently overlap, which makes it difficult to assign specific features to specific chemical components (Jha, 2010). Chemometric algorithms and multivariate data analysis are necessary to employ on the absorbance, transmittance or reflectance data to extract the desired chemical information. Furthermore, spectroscopic assessments only offer constituent gradient and are unable to provide information on the spatial distribution in the object. In order to get the spatial distribution, vision technique is a necessity. Computer vision technique had an earlier application in agriculture to identify plant species. With the rapid development of image processing technology and computer software and hardware, computer vision has been attracting much attention from the agri-food industry and being applied on quality inspection, classification and evaluation of a wide range of agri-food products (Zheng et al., 2006). The image data can reflect many external features such as color, shape, size, surface defects and contamination (Du and Sun, 2004). To date, computer vision has been extensively applied to solve various food engineering problems, ranging from simple quality evaluation of foodstuffs to complicated quality attributes ordinarily unavailable to human evaluators (Sun, 2008; Cubero et al., 2011). Despite the general utility of computer vision as a powerful inspection tool, their capabilities regarding more in-depth investigation of internal characteristics are fundamentally limited. This is due to the very limited spectral and multi-constituent information provided by this technique.

As an integrated alternative, hyperspectral imaging has opened up new possibilities within food analysis. Hyperspectral imaging can integrate the advantages of conventional digital imaging and spectroscopy to obtain both spatial and spectral information from an object simultaneously (Sun, 2010). This technology has recently been applied to evaluate internal and external attributes of various food and agricultural products including apple, peach, strawberry, tomato, cucumber, mushroom, wheat, walnut, etc. Fruits and vegetables have been evaluated for physical and chemical attribute such as firmness (Lu and Peng, 2006), presence of bruises (Lu, 2003; Xing and De Baerdemaeker, 2005), bitter pits lesions (Nicolaï et al., 2006), defects (Mehl et al., 2004), and chilling injury (Liu et al, 2006; ElMasry et al., 2009). Investigation on other products includes identification of freeze damaged mushroom (Gowen et al., 2009), healthy and damaged wheat kernel discrimination (Singh et al., 2010), and oil and oleic acid content prediction in corn kernels (Weinstock et al., 2006). The versatility of hyperspectral imaging has brought innovation to the food industry. Several review papers have been published mainly focused on food quality evaluation (Gowen et al., 2007; Nicolaï et al., 2007), however, a detailed summarization of applications of hyperspectral imaging in agricultural produce is still unavailable. Therefore, the objective of this paper is to introduce the fundamentals of hyperspectral imaging and mainly focus on its applications in the quality assessment of agricultural products.

FUNDAMENTALS OF HYPERSPECTRAL IMAGING

In order to use the hyperspectral imaging technology, a good understanding of the theory behind the technique is required. The history development, imaging acquisition system and data mining of the hyperspectral image technique are described in details in this part to allow the reader to gain a comprehensive knowledge about this technology.

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History Development

The concept of hyperspectral imaging originated in the 1980's, when A.F.H. Goetz and his colleagues at National Aeronautics and Space Administration (NASA) began a revolution in remote sensing by developing new imaging instruments (Goetz et al., 1985). Since the 1980s, the U.S. developed the first generation of Airborne Imaging Spectrometer (AIS) with 128 bands and spectral coverage within 1.2~2.4μm. In 1987, the Jet Propulsion Laboratory (JPL) developed a successful Airborne Visible / Infrared Imaging Spectrometer (AVIRIS), which became the representative of the second-generation hyperspectral imager (Goetz, 2009). After the success of AVIRIS, hyperspectral imaging gradually shifted from the research phase to the practical application stage. Apart from applications in remote sensing, hyperspectral imaging technology has spanned several areas such as applications in agriculture (Lawrence et al., 2003), pharmaceuticals (Roggo et al., 2005), and the food industry (Sun, 2010; Gowen et al., 2007).

Imaging Acquisition System

Main components of hyperspectral imaging system

A typical hyperspectral imaging system consists of the following components: a light source (illumination), a wavelength dispersion device (spectrograph), an area detector (camera), a translation stage and a computer as shown in Fig. 1. Light sources generate light that illuminates the target object. It is an information carrier and plays an important role for the performance and reliability of the imaging system. Wavelength dispersion devices are the heart of hyperspectral

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imaging system. Optical and electro-optical instruments are used for dispersing broadband light into different wavelengths. After interaction with the target and going through the spectrograph, light carrying useful information is eventually obtained by a detector by converting radiation energy into electrical signals. The spectral information is recorded on a 2D detector array. As the camera captures only a line of the illuminated object, a translation stage is used to move the sample past the objective lens. By scanning the entire surface of the specimen, a complete hyperspectral image is created and displayed by the computer.

Acquisition and storage modes of hyperspectral images

Hyperspectral images are three-dimensional (3-D) in nature. Generally there are three approaches to acquire one hyperspectral image: point scanning, line scanning and area-scanning, as illustrated in Fig. 2. The point scanning method known as “whiskbroom” produces hyperspectral images by measuring the complete spectrum of a single point (pixel) at a time. A single point is scanned along two spatial dimensions, then the sample moves to the next measurement point and another spectrum is captured. By moving the sample systematically in two spatial dimensions, a complete hyperspectral image can be obtained. The line scanning also known as ‘‘pushbroom’’ method can be considered as an extension of point scanning method. This method simultaneously acquires a line of spatial information as well as spectral information corresponding to each spatial point. The line-scan method requires the use of an imaging spectrometer where a diffraction grating disperses light entering through a thin slit and projects the spectrum onto a two-dimensional area detector. For each line-scan, a two dimensional (spatial and spectral) image is created. Repeating this process allows to build a 3-D image of the object. Each spectral image contains line pixels in spatial axis and spectral pixels in spectral axis. Pushbroom imaging is the most popular one for the food industry due to its readiness for on-line application. Both point scanning and line scanning are spatial-scanning methods. The area scanning method, on the other hand, is a spectral-scanning method. In area-scanning imaging, the hypercube is obtained by gaining spatial images at all wavelengths in sequence. The hyperspectral image is acquired one wavelength after another for the whole object by keeping the image field of view fixed. The 3-D hyperspectral image cubes acquired by point-scanning, line-scanning, and area-scanning methods are generally stored in the formats of band interleaved-by-pixel (BIP), band interleaved by line (BIL), band sequential (BSQ) format, respectively. The three data storage formats can be converted to each other (Sun, 2010).

Data Mining

The big advantage of hyperspectral imaging is the ability to characterize the chemical and structural properties of a sample by measuring the substantial amount of spectral pixels collected. However this extraordinary data posed considerable computational challenges. Efficient data mining is needed to extract the hidden information from these hypercubes. In this section, data structure, image calibration, spectral and image processing procedures will be addressed.

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Data structure

Fig. 3 illustrates the structure of a hypercube, which contains a stack of two-dimensional images at different wavelengths and can be described as I (x, y, λ). It can be viewed either as a spectrum I (λ) at each individual pixel (x, y) or as an image I (x, y) at each individual wavelength λ, Each image acquires spatially distributed spectral information at pixel levels and allows visualization of biochemical constituents of a sample. Each pixel contains the spectrum of that specific position. The resulting spectrum can characterize the composition of that particular pixel.

Image correction

The area detector in the hyperspectral imaging system records digital counts of radiance from the target known as uncorrected radiance. Because of the differences in camera quantum and physical configuration of imaging systems, the uncorrected radiance for different systems may not be the same even when imaging the same target under the same imaging condition. Therefore, the original hyperspectral images should be corrected into the reflectance mode based on black and white reference images. The acquired hyperspectral images can be corrected using the following equation (ElMasry et al., 2009; Mehl et al., 2004):

$$R_c = \frac{R_0 - B}{W - B} \times 100 \qquad (1)$$

where R_C is the corrected hyperspectral image in a unit of relative reflectance (%), R_0 is the original hyperspectral image, B is the dark image (~0% reflectance) and W is the white reference image (~99.9% reflectance).The dark reference B is used to remove the dark current effect of the area detectors, which can be obtained by turning off the light source and completely covering the lens with its opaque cap. The white reference W is normally acquired from a Teflon white surface under the same condition of the raw image.

Spectral processing

Most absorption bands in the near infrared region are composed of a large set of overtone or combination bands due to vibrational and rotational transitions. In agricultural products, the multiple bands and the effect of peak-broadening cause the near infrared spectrum to be highly convoluted. Furthermore, the spectrum may further be complicated by instrumental noise, complex chemical composition of products, environmental factors and other sources of variability. As a consequence, it is difficult to differentiate specific absorption bands. Therefore, the data mining of numerous spectral data with chemometrics is necessary to extract the hidden information in the NIR spectrum (Cen and He, 2007). The whole data processing generally consists of the following several steps (Fig. 4): spectral preprocessing, calibration model and model validation.

Preprocessing

The target of spectral preprocessing is to remove the undesirable effects (i.e., light scattering, path length variation and background noise) from the spectral information prior to multivariate modeling to obtain reliable and stable calibration models (Rinnan et al., 2009). In the field of hyperspectral imaging, a number of spectral preprocessing techniques exist such as smoothing,

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scatter correction, and derivatives. Savitzky–Golay smoothing is one of the most known smoothing methods often used to eliminate noise (Pontes et al., 2006). Scatter correction is needed to avoid the light scattering in NIR spectroscopy. Standard normal variate (SNV) and multiplicative scatter correction (MSC) are widely applied for scatter minimization (Luypaert et al., 2004). SNV transformation is capable of removing the slope variation from spectra caused by scatter. MSC is based on the idea of correcting the scatter level of all spectra of a group of samples to the level of an average spectrum. Derivative is used to remove overlapping peaks and baseline shifts induced by the variation of particle sizes and instrumental conditions, so that more details within the spectra can be revealed (Rinnan et al., 2009).

Calibration model

Many calibration models have been developed to extract spectral information (Geladi and Dabakk, 1995). In general, multivariate chemometrics applied in spectral data can be divided into quantitative analysis with multivariate regression and qualitative analysis with multivariate classification as shown in Fig. 4.

The multivariate regression techniques aim at establishing a relationship between a desired physical, chemical or biological attributes of an object and its observed spectral response. The most widely used multivariate regression methods in quantitative analysis are MLR (multiple linear regression), PCR (principal component regression), and PLSR (partial least square regression) (Blanco et al., 1999). In MLR analysis, the quality attribute values are approximated by establishing a relationship between the response variable and observed spectral variables. The regression coefficients are estimated by minimizing the error between the predicted and observed response values in a least squares sense. MLR models typically do not perform well because of high co-linearity of the spectra and easy loss of robustness of the calibration models (Wu et al., 2012). PCR is a two-step multivariate method that first decomposes the spectral value by principal component analysis followed by fitting with a MLR using selected principal components as predictors (Nicolaï et al., 2007). The regression on the selected PCs avoids co-linearity and reduces the dimensionality of the regressors. PLSR is another reliable method for multivariate calibration, especially when there is a large amount of correlation among spectral variables. It uses fewer numbers of latent variables than PCR and can predict several quality attributes (Wold et al., 2001).

Qualitative analysis with multivariate classification is also an important issue in hyperspectral analysis, especially for the food industry (Kim et al., 2000). Multivariate classification can be supervised or unsupervised. Supervised classifications refer to techniques in which a prior knowledge about the category individual of samples is used for classification. On the other hand, unsupervised classification techniques develop classification labels automatically without knowing any foreknowledge of the classes and mainly seek out similarity between key features of image data by using some clustering algorithms. There are numerous multivariate classification methods available for hyperspectral data, such as PCA (principal component analysis), KNN

(K-nearest neighbors), ANN (artificial neutral network), SVM (support vector machine) and. SAM (spectral angle mapper). PCA is the most frequently used unsupervised classification technique which uses an orthogonal transformation to convert correlated variables into linearly uncorrelated variables called principal components (PC). The first few principal components have the largest possible variance and can be used as inputs to multivariate techniques, instead of the original variables (Nicolaï et al., 2007; Xing et al., 2007). KNN is another unsupervised classification method. It is a very simple learning algorithm. The dataset is classified by minimizing the sum of squares of distances between each category and the corresponding cluster centriod (Shawe-Taylor and Cristianini, 2004). Despite its simple implementation, it is sensitive to noisy or irrelevant attributes, which can result in less meaningful classification. In supervised classification, ANN is a powerful modeling tool for classifying objects using their features. For food quality evaluation, ANN is usually used to model complex relationships between the physical properties and quality factors. The multilayer feed forward neural network is widely used with the spectral value as the input layer and the predicted quality attributes as the output layer. Through successive learning from the training data, the network learns to predict the relationships (Næs et al., 1993). The multi-layer perceptrons (MLP) and feature tree are two kinds of classifiers used in ANN. MLP is widely used in prediction, classification and modeling problems. It is formed by non-linear elements arranged in layers. A MLP with two hidden layers can establish any relationship between input and output data (Fernandez-Redondo et al., 2004). MLP was employed by Kim et al. (2000) to classify kiwi fruit grown under different conditions using linear and non-linear pattern recognition modes. It was concluded that ANN based on MLP appeared to be well suited to the classification of fruit grown or stored under different conditions. In addition, ElMasry et al. (2009) analyzed visible and near-infrared hyperspectral data with a neural network based on MLP for the detection of chilling injury in apple. They reported that 98.4% of the injured apples were properly detected. As another classifier of ANN, feature tree is a non-parametric statistical method widely employed in general classification and regression problems. A feature tree is an infinite tree with marked features and with marked nodes. Each feature can be decomposed into several alternative sub-features. Each node is labeled with a set of features representing different properties (Webb, 2002). Classification methods based on feature tree generally provide good results in classification problems. For example, Gómez-Sanchis et al. (2012) detected rottenness in citrus fruits through analysis of hyperspectral data using ANN classifiers based on feature tree. A classification accuracy of 98% was achieved, which demonstrated the suitability of the proposed approach. SVM is a well-suited high-dimensional supervised classification method that is recently developed in data mining applications. With SVM, classes are not characterized by statistical criteria but by a geometrical criterion. SVM performs classification by constructing an N-dimensional hyperplane that optimally separates the data into two categories. SVM can help to evaluate more relevant information in a convenient way and is also capable of handling nonlinear classification cases (Zhao et al., 2006). To minimize illumination effects of image data, SAM supervised algorithm is a first choice classification method which uses an n-dimensional angle to match pixels to reference spectra. This method determines the spectral similarity by the vector direction instead of vector length. The angle between the endmember spectrum vector and each pixel vector in n-dimensional space is used for classification (Park et al. 2007). SAM algorithm was employed by Yao et al. (2010) for classifying single corn kernels into aflatoxin contaminated and healthy groups using fluorescence hyperspectral image. The classification accuracy of 86% and 88% was achieved for 20 ppb (parts per billion) human consumption level and 100 ppb feed level, respectively. The results indicated that the SAM method and fluorescence hyperspectral imagery have the potential to classify aflatoxin contaminated corn kernels.

Another important technique for analyzing hyperspectral data is to perform an analysis of variance (ANOVA). ANOVA is used to examine the variance of dependent variables by decomposing the variability in the response variable amongst the different factors. In the analysis, total variance is partitioned into factor-related components and measurement error with the goal of quantifying significant sources of variation (Bock et al., 2010). Several studies have used ANOVA to investigate magnitude of variation or error in estimates or measurements. A recent study using ANOVA to analyze early detection of toxigenic fungi on maize was reported by Fiore et al. (2010). ANOVA were used to assign variance to the wavelengths that have the highest correlation, and the results showed that ANOVA and Fisher's test allowed identification of two wavelengths (410 nm and 470 nm) characterized by a high discriminating power concerning the fungal presence and/or growth on maize kernels. Using a similar approach with ANOVA, A multi-spectral fluorescence image in linear combination with a pair of selected wavebands based on the results of ANOVA analysis was able to detect defective cherry tomatoes with >99% accuracy (Cho et al., 2013). This detection algorithm is expected to be used for on-site and real-time multi-spectral systems.

Model validation

Validation procedures are necessary to assess the accuracy of the calibration model and to avoid overfitting. The quality of calibration models can be evaluated by correlation coefficient (*R*), standard error of calibration (SEC), standard error of prediction (SEP), and root mean square error estimated by cross-validation (RMSECV). A good model should have a lower value of SEC, SEP, and RMSECV as well as higher value of R and a small difference between SEC and SEP (Nicolaï et al., 2007). Different methods in spectral preprocessing and calibration modeling as mentioned above should be investigated for the establishment of useful calibration models.

Image processing

Image processing plays an important role in hyperspectral data analysis. Owing to the imperfections of the image acquisition systems, the images acquired are subject to various defects that will need subsequent processing. A typical image processing task involves a series of steps, which can be grouped into three major stages as depicted in Fig. 5. These include image

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preprocessing, segmentation, and feature extraction. The purpose of image preprocessing is to improve the quality of the obtained images, which are often degraded by low contrast and noise in the optical and electronic systems. The frequently used preprocessing methods include histogram equalization, filtering, transformation, and arithmetic operations (Gonzalez et al., 1987). Image segmentation is another essential step to partition an image into component parts, in which the pixels have similar image characteristics. Proper segmentation is very critical, as the segmented image could be very useful for identifying the region of interests (ROIs) in the tested objects, thus facilitating the obtaining of some useful information pertaining to the desired features (ElMasry et al., 2009). Once the image is successfully segmented, further processing and analysis can be realized by deciphering image data from the complex images. Generally, images are stored and processed in the form of matrices formed by pixels. The location of pixels in images can be served to obtain geometric information (size and shape) of the object while the pixel intensity value can be used to extract the surface information of the objects, including color and texture (Sun., 2008). Different operations are usually carried out at this stage to extract desired information from the image or to highlight the variation among different regions of the image. Textural feature extraction based on gray-tone spatial dependencies for image classification is one example of the image processing algorithms (Haralick et al., 1973). In addition, the generation of chemical images in a pixel-wise manner is an important way of processing hyperspectral image. The chemical images display concentration gradients of certain components of food products and thus provide a quantitative visualization of food quality variations (ElMasry et al., 2008a; Kamruzzaman et al., 2012).

APPLICATIONS

Originally developed for remote sensing applications, hyperspectral imaging technology has recently found widespread use for quality evaluation of agricultural products, especially for the comprehensive testing of the internal and external qualities. The following sections will give a summarization of the main recent research conducted in this aspect.

Fruits and Vegetables

Fruits and vegetables are one of the main components of human diet. They provide abundant nutritional elements for human body. Therefore, both buyers and consumers attach great importance to the quality of fruits. The quality of fruits can be determined by many physical and chemical attributes such as firmness, presence of bruises, dry matter, organic acid, soluble solids content, pH, and sugar contents. These factors not only affect the taste and color of fruit, but also act as a prerequisite for synthesis of fruit vitamin. Traditional analytical methods used for quality measurement are destructive, laborious, and time consuming, which prohibits quality automation measurement and classification technology. To meet the quality requirements and to improve competition of fruit production industry, rapid, non-destructive, and automated inspection and grading systems are essential (Lorente et al., 2012). Hyperspectral imaging is an emerging, non-contact analytical technique which has found widespread use in assessment of quality properties of various kinds of fruits and vegetables, the applications involves determination of internal and external quality attributes as well as detection of various contaminations (Table 1).

Internal quality attributes

Fruits and vegetables with good quality are under increasing demand by consumers. To monitor and control quality, the quality-related attributes encompassing sensory attributes, nutritive values, and chemical constituents have to be detected. Attempts on using hyperspectral imaging as a non-destructive method for assessing internal quality attribute of fresh fruits and vegetables have been investigated by many authors. The majority of the studies are focused on detection of firmness and soluble solids content (SSC) (Noh and Lu, 2007; Peng and Lu, 2008; Liu et al., 2008; Tallada et al., 2006; Qin et al., 2009; Mendoza et al., 2011) because firmness and SSC are considered as two important attributes in assessing post-harvest quality of fruits and directly influence shelf life and consumer acceptance. Researchers have utilized hyperspectral imaging systems for predicting firmness and SSC of various fruits. For instance, Nagata et al. (2005) developed models for prediction of firmness and SSC of strawberries using NIR hyperspectral imaging in the spectral range of 650-1000 nm. The three-wavelength models at 915, 870, and 765 nm for firmness prediction had a correlation accuracy of 0.786. For predicting firmness and SSC of apples, fluorescence images of 'Golden Delicious' apple was acquired by Noh and Lu (2007). A good prediction of firmness (R=0.76) was obtained by using PCA in conjunction with ANN,

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however, poor predictions were obtained for soluble solids content. Furthermore, Liu et al. (2008) used hyperspectral laser-induced fluorescence imaging technique (700-1100 nm) to measure SSC of orange. A correlation coefficient of prediction of 0.998 and 0.96 was obtained for SSC of 'Nanfeng' orange and navel orange, respectively. Besides, light scattering features of fruits is also potentially useful for assessing fruit firmness and SSC. Lu and Peng (2006) investigated hyperspectral scattering profiles (600-1000 nm) as a means for measuring peach fruit firmness. A two-parameter Lorentzian distribution (LD) function was used for prediction and the best prediction model was obtained at a wavelength of 677 nm. Best firmness predictions were obtained with a correlation coefficient of 0.77 and 0.58 for "Red Haven" and "Coral Star" peaches, respectively. In another research, Mendoza et al. (2011) investigated firmness and SSC prediction for apples by integration of spectral and image features extracted from the hyperspectral scattering images over the wavelength region of 500-1000 nm. Compared with the reflectance mode, the SEP for 'Golden Delicious', 'Jonagold', and 'Delicious' apples was reduced by 6.6, 16.1, 13.7% for firmness, and by 11.2, 2.8, and 3.0% for SSC, respectively. Hyperspectral scattering is an effective means for rapid, nondestructive estimation of fruit firmness and SSC.

Moreover, in terms of internal qualities, some other attributes were also studied. Zhao et al. (2009) have attempted to detect sugar content in apple by employing HSI technique with wavelength range within 685-900 nm. The PLSR method was used to produce the calibration and prediction model from their spectra. Predictions with correlation coefficient (R) of 0.91 were obtained for sugar content. Baiano et al. (2012) examined the possibility of applying the hyperspectral imaging technique for prediction of some physico-chemical and sensory indices of table grapes. PLSR model showed good correlations between each of the physico-chemical indices and the spectra information. In another study conducted by Fernandes et al. (2011), the estimation of grape anthocyanin concentration using hyperspectral data was explored, a squared correlation coefficient of 0.65 between estimated and measured anthocyanin concentration was obtained.

External quality attributes

Apart from the internal qualities, the outer appearance of fruits and vegetables affects consumer buying behavior. The presence of defects not only affects the appearance but also accelerates fruit and vegetable spoilage (Xing et al., 2007). The defects in fruit and vegetable include bruises, chilling injuries, contamination, canker, pits and rottenness. Bruise is the most common surface injury recorded on all fruit types and is also the main reason for rejecting fruits in sorting lines. Generally, severely injured fruits and vegetables are easy to identify visually. However, mechanical injury often causes hidden internal physical damage to fruit that is difficult to detect by human inspectors. As a result, HSI technique can be considered as a useful tool for detecting quality defects. The most popular agricultural commodities studied for bruise detection are apples. For detection of bruises in 'Golden Delicious' apples, Xing et al. (2005) employed a HSI system in 400-1000 nm to study its potential for detecting bruises. By using PCA method, an accuracy of about 86% was achieved for bruises detection. In a continued study, they made a comparison of PCA and PLSDA procedure for extracting the useful information from the hyperspectral images. They found PLSDA had more potential as compared with PCA for detecting bruises (Xing et al., 2007). Moreover, in terms of bruise detection, some other fruits and vegetables were also studied including strawberry (Nanyam et al., 2012), cucumbers (Ariana et al. 2006) and mushroom (Gowen et al. 2007). Among these studies, PCA were frequently used to detect bruise-damaged regions.

Chilling injury is another external damage to fruit and vegetables. Symptoms of chilling injury include brown staining, pitting, increased decay and quality deterioration. The occurrence of chilling injury leads to the physiological dysfunction of fruits and vegetables during the growing season, transportation, distribution, or storage. For detecting chilling injury in apples, ElMasry et al. (2009) used ANN to select the optimal wavelength and detect firmness changes due to chilling injury. An average classification accuracy of 98.4% for distinguishing normal and injured apples was achieved. The chilling injury on the citrus fruit was explored by Menesatti et al. (2005) using hyperspectral VIS-NIR imaging (400-970 nm). PLS regression analysis was applied for constructing a predictive model and acquired 95% of correct classification. For detection of chilling-induced damage in whole cucumbers, Liu et al. (2005) attempted to discriminate the ROI spectra of good cucumber skins from those of chilling injured ones by simple band ratio algorithms and PCA and a success rate of over 90% was achieved. Additionally, Gowen et al.

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(2009) investigated the potential of HSI technique for detecting freeze-damage of mushroom. They succeeded in early detection of freeze damage in white button mushrooms by multivariate analyses (PCA models) with classification accuracy of 97.9%. Apart from the chilling injury detecting studies introduced above, some studies dealt with comprehensive defects such as rotteness or sour skin detection. The rottenness in mandarin was investigated by Gómez-Sanchis et al. (2008). The detection was conducted under ultraviolet illumination using a HSI system (730-1020 nm). Linear discriminant analysis (LDA) and classification and regression trees (CART) were employed to reduce the number of detection wavebands. The rate of success achieved in classifying rotten fruit was above 91%. Furthermore, a shortwave infrared HSI system was explored to detect sour skin in onion by Wang et al. (2012). PCA was conducted on the spectra of the healthy and sour skin-infected onions. SVM classifier with three image features as input variables achieved 87.14% classification accuracy.

Contamination detection

Contamination of fruits and vegetable products is commonly viewed as a potential risk for infection with pathogens such as *Salmonella* and *Escherichia coli* as a result of exposure of the products to fecal materials during or after processing. Early detection of foodborne contamination of fruits and vegetables can be useful to prevent the intake of contaminated products. The variations of appearance and components in fruits may affect the successful identification of fecal contamination. To eliminate such influence, employment of chemometric algorithms and multivariate data analysis is necessary. For instance, PCA was used by Kim et al. (2002) for transforming hyperspectral dataset into principal components (PCs) that represent the overwhelming majority of the contaminants information of apples, four multispectral bands (450, 530, 685, and 735 nm) was chosen as the optimal bands to discriminate contaminated apple surfaces. In a continuous study (Kim et al., 2007), a HSI system in fluorescence and reflectance mode was used for detection of fecal spots on apple surface. By two-band ratio method, detection rate of fecal spots achieved was 100% and 99.5% by fluorescence and reflectance imaging, respectively. Another fluorescence system was used for fecal contamination detection of cantaloupe (Vargas et al., 2005). Optimal wavelengths were identified by PCA in their study for development of a multispectral detection system. Not limited in fruits, HSI were also used to detect feces on vegetables (Yang et al., 2010; Siripatrawan et al., 2011, Kang et al., 2011). Yang et al. (2010) employed a hyperspectral fluorescence imaging system (320-400 nm) for detection of bovine fecal contaminants on the abaxial and adaxial surfaces of romaine lettuce and baby spinach leaves. The two-band ratio, 666 nm/680 nm was used to differentiate the contaminated spots from uncontaminated leaf area and accurately detected all contaminated spots. Siripatrawan et al. (2011) employed ANN method to construct a prediction map of all pixel spectra and provided a quantitative visualization of *E. coli* variations in packaged fresh spinach.

Grains

Attempts on using HSI for assessing quality attribute of some grain products have been investigated by several authors. The studies mainly focused on three aspects: grain classification and identification, damage and contaminant detection, constituent concentration prediction (Table 2). Grain classification is one of the important challenges to the grain industry. Grains can be classified by visual inspection based on their colour, growing season, hardness, etc. Such inspection suffers from some disadvantages, for example, some grain classes may look similar, but their chemical composition can vary significantly, which will affect the end-product quality. Development of a rapid method to identify grain classes would be of great benefit to producers, grain handlers and consumers. The tremendous development and remarkable improvements in HSI technique has met this requirement. A number of studies have proved the usefulness of HSI for wheat class differentiation. In the study of Mahesh et al. (2008), accuracies of 94-100% and 86-100% were obtained from LDA and quadratic discriminant analysis (QDA) models for classification of wheat grown in western Canada. Recently, classification of oat and groat kernels using HSI system was realized by Serranti et al. (2013). They proposed an optimal classification model based on a reduced set of three wavelengths (1132, 1195 and 1608 nm). This technique greatly speeds up the classification processing for industrial applications. HSI was also used to discriminate healthy wheat kernels from damaged kernels by Singh et al. (2009). An accuracy of 85-100% in classification was achieved by using LDA and QDA. Another study conducted by the same author (Singh et al., 2010) assessed the potentiality of short-wave NIR hyperspectral imaging for detecting midge-damaged wheat kernels and obtained a high accuracy of 95.3-99.3%

in classification. Besides, HSI was also used for nut classification. Discrimination of black walnut shell and pulp using hyperspectral fluorescence imaging (425-775 nm) was investigated by Jiang et al. (2007). Gaussian-kernel based support vector machine (SVM) approach was used for the classification and an overall 90.3% recognition rate was achieved. Moreover, the transmission spectra of almond nuts were used to discriminate internally damaged almond nuts from normal ones by Nakariyakul et al. (2011). Two sets of ratio features (850nm/1210nm and 1160nm/1335nm) were used for classification. This proposed method minimizes the misclassification rate. In addition, Williams et al. (2009) attempted the maize kernel classification by using HSI system and multivariate data analysis. The detection of glassy (hard) and floury (soft) endosperm inside the kernels using PCA analysis was achieved. For the contaminant detection and constituent concentration prediction for the grain products, Williams et al. (2012) tracked changes in fungal contamination of whole maize kernels by application of NIR hyperspectral imaging. The results proved the possibility of predicting infection degree by establishing PLS models with a limited number of spectra. For oil and moisture content prediction in corn kernels, Cogdill et al. (2004) employed a NIR hyperspectral imaging system in transmission mode. PLS and PCR were used to develop predictive calibrations. Standard error of cross-validation (SECV) of 1.20% and 1.38% were achieved for moisture and oil calibrations, respectively. Prediction of constituent concentration of maize kernels by HSI technique is possible.

CHALLENGES

HSI is a powerful technique for predicting essential properties in agricultural products such as fruit firmness and SSC, chilling injury, bruise detection and fecal contamination. It can replace traditional imaging or spectroscopy in situations where simultaneous measurements and visualization of different quality attributes are required. However, HSI does encounter some barriers to its widespread adoption in the food industry. HSI only has limited ability for estimating multiple quality defects and diseases, mainly due to the highly complex nature of the damaged or diseased samples and the low adaptability of the multivariate models. Consequently, future development of HSI requires a better improvement of robustness of correlation models. Another challenge in hyperspectral image technique is the issue of high-dimensional nature of hyperspectral data. Currently, there exist many chemometric methods to tackle the hyperspectral datasets. However, the high-dimensionality of hyperspectral data introduces significant limitations in the data processing. There is a need to develop cost-effective and efficient algorithm to speed up algorithm performance and to satisfy the extremely high computational requirements of hyperspectral applications. Besides, most available hyperspectral data processing techniques focus on analyzing the data without incorporating information on the spatial data. The design of techniques able to fuse the spatial and spectral data simultaneously is an important future development trend of hyperspectral imaging. Other practical issues of sensor costs, data storage and image acquisitions will need to be addressed for operational uses and thus enabling real-time quality monitoring by HSI system.

CONCLUSIONS

The results of previous research works presented in this review confirmed that HSI techniques are well suited for measuring quality attributes of agricultural products. As a combination of spectroscopy and traditional imaging, HSI can obtain both spatial and spectral information from food products in a form of spatially organized spectroscopy at the same time. Such richness in information provides a broad platform for applying various chemometrics methods for qualitative and quantitative analysis to display chemical composition and external features of agri-food. However, improvements are needed to address the issue of high dimensionality of hyperspectral data, which could limit their implementations for on-line systems. As a comparison to a hyperspectral image system that has voluminous data and high cost, a multispectral imaging system with a limited number of wavebands has the capability to meet the needs of real-time acquisition and processing. Therefore, further exploitation of HSI systems should be to find optimal wavelengths and develop efficient algorithms for many food commodities. With selected optimal bands and powerful algorithms, their on-line or real-time applications can be realized in multispectral imaging systems. It is also expected that HSI systems will find more substantial and widespread applications in food safety monitoring and control in different food production stages.

ACKNOWLEDGEMENTS

The authors gratefully acknowledge the financial support received from China Postdoctoral Fellowship scheme. The authors are also grateful to the Guangdong Province Government (China) for support through the program of “Leading Talent of Guangdong Province (Da-Wen Sun)”.

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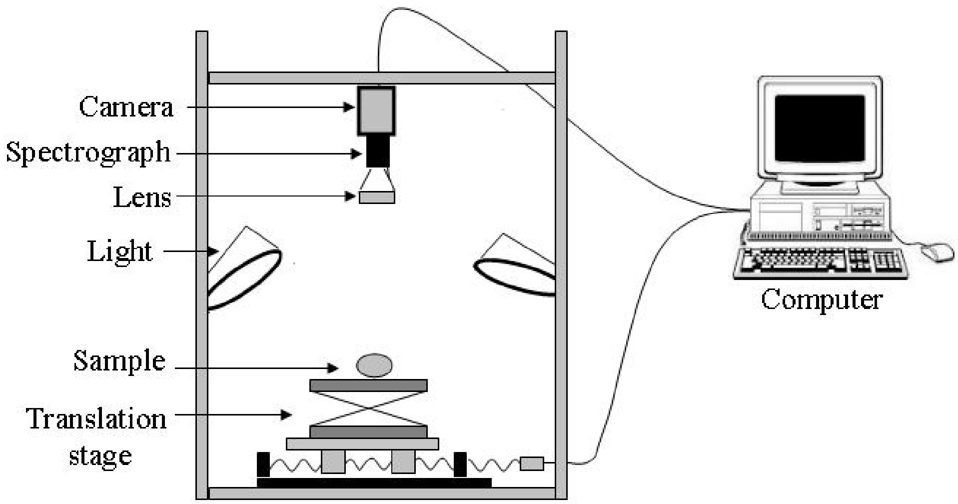

Figure 1 A schematic of a typical hyperspectral imaging system

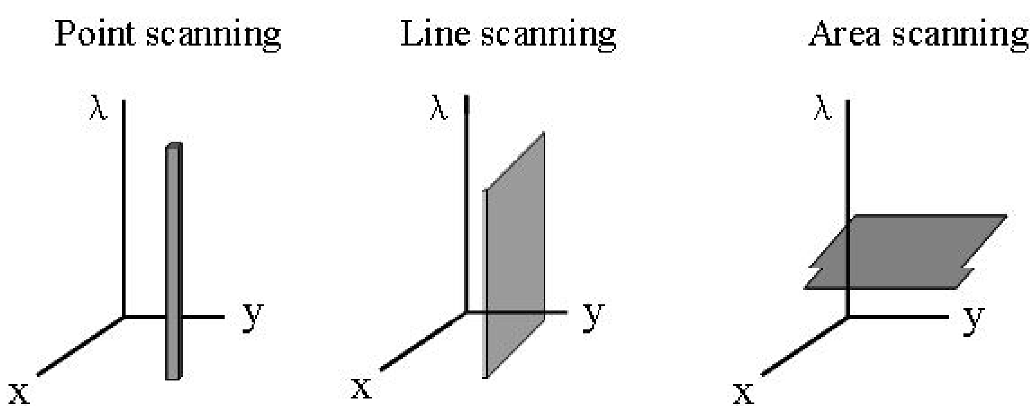

Figure 2 Methods for acquiring hypercube containing spatial (x and y) and spectral (λ) information. (Sun, 2010)

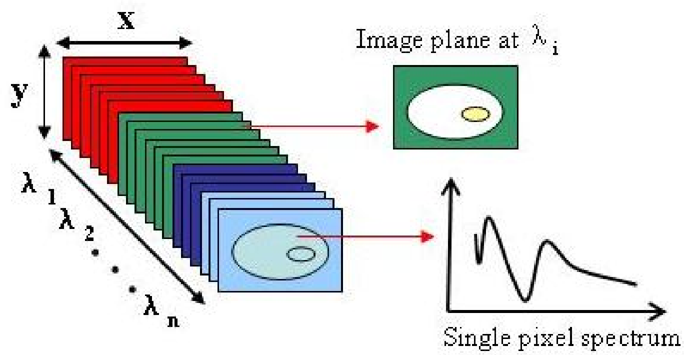

Figure 3 Hypercube contains two spatial (x_i,y_j) and one wavelength (λ_i) dimension

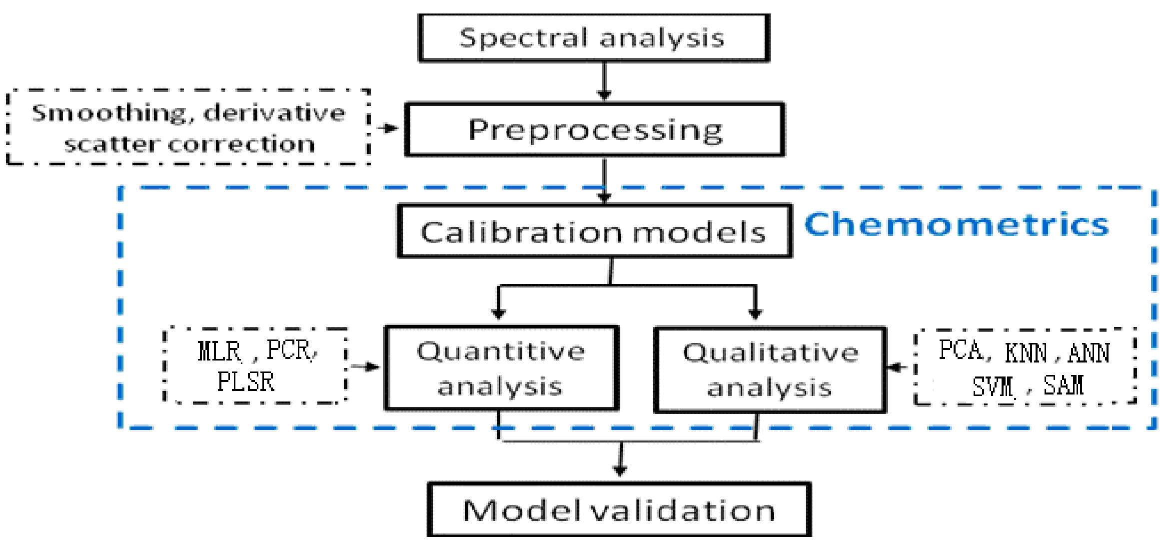

Figure 4 Spectral data analysis. MLR: multiple linear regressions, PCR: principal component regression, ANN: artificial neural network, KNN: K-nearest neighbors, SVM: support vector machine, SAM: spectral angle mapper

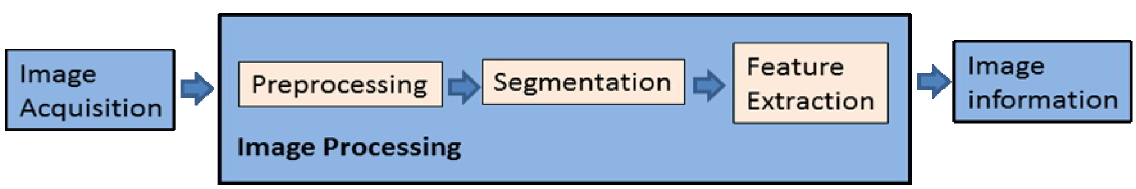

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Figure 5 Basic step in image processing

Table 1 Applications of hyperspectral imaging for quality assessment of fruits and vegetables

	Products	Quality attributes	Mode	Spectral range	Data analysis	Accuracy	Reference
Fruits	Apple	Firmness and SSC	F	500–1040	ANN	0.74-0.94	Noh and Lu, 2007
		Firmness and SSC	S	450–1000	MLR	0.88-0.89	Peng and Lu, 2008
		Firmness and SSC	A/ S	500–1100	MLR	0.75-0.86	Qin et al., 2009a
		Firmness and SSC	S	500-1000	PLS	0.67-0.95	Mendoza et al., 2011
		Bruise detection	R	400–1000	PCA	86.0%	Xing et al., 2005
		Bruise detection	R	400–1000	PCA-PLSDA	86.36%	Xing et al., 2005a
		Bruise detection	R	400–1000	PCA	93.95%	ElMasry et al., 2008
		Contaminant detection	R	430–900	BD	-	Mehl et al., 2004
		Contaminant detection	R	430–930	BR	100%	Liu et al., 2007
		Contaminant detection	R	400–1000	PCA	-	Kim et al., 2002
		Contaminant detection	R/ F	400–1000	BR	99.5%,100 %	Kim et al., 2007
		Bitter pit detection	R	900–1700	PLS	-	Nicolai et al., 2006
		Chilling injury	R	400–1000	ANN	98.4%	ElMasry et al., 2009
		Sugar content	R	685–900	PLS	0.91	Zhao et al., 2009
		Starch index	R	1000–170	PLS-DA	80.8%	Menesatti et al., 2009

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	Citrus	Chilling injury	R	400-970	PLSR	95%	Menesatti et al., 2005
		Canker	R	450 - 930	SID	96.2%	Qin et al., 2009
		Rottenness	R	400-1100	ANN	98%;	Gomez-Sanchis et al., 2012
	Strawberry	Bruises detection	R	650–1000	ANN	90.7%	Nagata et al., 2005
		Firmness	R	650–1000	MLR	0.79	Tallada et al., 2006
		TSS and MC	R	400–1000	MLR	0.80 − 0.87	ElMasry et al., 2007
		Bruise detection	R	960-1700	DFS	-	Nanyam et al.,2012
	Peach	Firmness	S	500-1000	MLR	0.99	Lu and Peng, 2006
		Sugar content	R	650–1000	PLS	0.97	Guo et al., 2007
	Grape	acidity , SSC	R	400–1000	PLSR	0.8-0.95	Baiano et al., 2012
		AC	R	400- 1000	ABNN	0.65	Fernandes et al., 2011
	Cherry	Pits	T	450-1000	ANN	98.4%	Qin and Lu, 2005
	Orange	SSC	F	700–1000	MLR	0.96-0.99	Liu et al., 2008
		Defects	R	400 - 1000	PCA, BR	91.5% 93.7%	Li et al., 2011
	Mandarin	Rottenness	R	730 -1020	LDA,CART	89.2%,91.2%	Gomez-Sanchis et al., 2008
	Cantaloupe	Fecal contamination	F	425-774	PCA	79 -96%	Vargas et al., 2005
	Blueberry	Foreign materials	R	908 -1724	DA	-	Sugiyama et al., 2010
Vegetables	Cucumber	Bruise	T	450-950	PLS-DA	98.7%	Ariana and Lu, 2008
		Chilling injury	R	447-951	PCA-FLD	91%	Cheng et al., 2004
		Chilling damage	R	447-951	BR-PCA	90%	Liu et al., 2005
		Defect , color	R/T	400-1000	PCA	86%	Ariana et al., 2010

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Mushroom	Chilling injury	R	400-1000	PCA-LDA	97.9%	Gowen et al., 2009
	Bruise detection	R	400-1000	PCA	-	Gowen et al., 2007a
	moisture content, colour, texture	R	400-1000	MLR-PCR	-	Gowen et al., 2008
Potato	Cooking time	R	400-1000	PLSDA	0.94-0.96	Nguyen Do Trong et al., 2011
Rape	Seed yield	R	380-1030	PLSR	0.71	Zhang et al., 2012
Onion	Sour skin disease	R	950–1650	PCA,SVM	87.14%	Wang et al., 2012
Spinach	Fecal contamination	F	416-700	PCA, MF, thresholding	-	Kang et al., 2011
	Contamination	R	400–1000	PCA-ANN	0.97	Siripatrawan et al., 2011
Pepper	Contamination	R	400-600	LDB	80%	Kalkan et al., 2011

A: absorption, F: fluorescence, R: reflectance, S: scattering, T: transmittance, BD: band difference, BR: band ration, SID: spectral information divergence; DFS: decision-fusion strategy, ABNN: adaptive boosting neural network, CART: classification and regression trees; AC: anthocyanin content TSS: total soluble solids, MC: moisture content, MF: Mean filter; SG Filter: Savitzky-Golay filter, FLD: Fisher's linear discriminant, LDB : local discriminant bases

Table 2 Applications of hyperspectral imaging for grains quality evaluation

Products	**Quality attributes**	**Mode**	**Spectral range**	**Data analysis**	**Accuracy**	**Reference**
Wheat	Classification	R	960-1700	LDA, QDA, ANN	96%, 93%, 90%	Mahesh et al., 2008
	Classification	R	960–1700	LDA	99.1%	Choudhary et al., 2009
	Classification	R	1000–1600	MVI	85-100%	Singh et al., 2009
	Classification	R	700–1100	MVA	95.9-99.3%	Singh et al., 2010
	Classification	R	1006–1650	PLS-DA	100%	Serranti et al.,2013
Maize/corn	Detect toxigenic fungi	R	400–1000	PCA-DA	97.0%,94.5%	Del Fiore et al., 2010
	Hardness	R	960–1662 1000–2498	PLS-DA	-	Williams et al., 2009
	Fungal development	A	1000–2498	PCA-PLSR	-	Williams et al., 2012
	constituent concentration	T	750-1090	PLS	SECV,1.2%	Cogdill et al., 2004
	Oil and oleic acid	R	950-1700	PLS	RMSEP, 0.7%	Weinstock et al., 2006
Walnut	classify shell and pulp	F	425 -775	SVM	90.3%	Jiang et al., 2007
Almond nut	Classification	T	700 - 1400	BF	91.2	Nakariyakul et al., 2011
Semolina	Detecting insect	R	900-1700	PLS	0.99	Bhuvaneswari et al., 2011
Soybean	Sweetness, amino acid	R	400-1000	ANN	0.61-0.74	Monteiro et al., 2007

MVI: multivariate image analysis, MVA: machine vision algorithms, QDA: quadratic

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discriminant analysis, RF: ratio feature.

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