Journal of Food Engineering 169 (2016) 155–164

Contents lists available at ScienceDirect

Journal of Food Engineering

journal homepage: www.elsevier.com/locate/jfoodeng

Review

Application and potential of backscattering imaging techniques in agricultural and food processing – A review

Segun Emmanuel Adebayo [a], Norhashila Hashim [a,*], Khalina Abdan [a], Marsyita Hanafi [b]

[a] Department of Biological and Agricultural Engineering, Faculty of Engineering, Universiti Putra Malaysia, 43400 Serdang, Selangor, Malaysia
[b] Department of Computer and Communication Engineering, Faculty of Engineering, Universiti Putra Malaysia, 43400 Serdang, Selangor, Malaysia

A R T I C L E I N F O

Article history:
Received 14 February 2015
Received in revised form
6 August 2015
Accepted 6 August 2015
Available online 21 August 2015

Keywords:
Diffuse reflectance
Non-invasive
Optical properties
Fruit quality
Scattering

A B S T R A C T

This review covers the application of backscattering imaging as a non-invasive technique for monitoring the quality of agricultural and food products. The review enumerates and discusses the concepts and various applications of laser light backscattering imaging (LLBI), multispectral laser backscattering imaging (MBI) and hyperspectral laser backscattering imaging (HBI). All the methods make use of laser light which varies in spectrum from visible up to near-infrared to detect changes in the quality of fresh produce. Emphasis is placed on applications which demonstrate promising potential for agricultural and food applications under various conditions. A critical review of the limitations is also given.

Contents

1. Introduction

The increasing demand for agricultural and food commodities has brought about the adoption of automation and modern techniques to increase the rate of production, improve quality assessment and reduce waste. The increasing rate of international trade has imposed a high-level of standardisation in terms of quality and safety of these commodities among the countries involved (Greensill and Newman, 1999). The various handling stages and processes to which these commodities are subjected, including environmental conditions, affects their quality. It is therefore important to monitor and control the quality of these commodities to ensure that they adhere to a defined set of quality criteria or to meet consumer requirements (Ruiz-Altisent et al., 2010).

The quality index of agricultural and food commodities comprises attributes which facilitate their acceptance or rejection by the consumer (Singhal et al., 1997). Choi et al. (2006) reported the use of appearance, texture, nutritional content, flavour, and defects

* Corresponding author.
E-mail address: norhashila@upm.edu.my (N. Hashim).

http://dx.doi.org/10.1016/j.jfoodeng.2015.08.006
0260-8774/

as five major attributes to assess the quality of fresh produce. Many reference techniques have been developed to investigate produce quality. Most of the techniques are subjective and destructive. Hence measurements usually are time consuming, lack consistency and often lead to waste. Thus, efforts have been made in recent years which focus on developing non-destructive techniques to overcome the stated problems (Mollazade et al., 2012).

Non-destructive optical-based techniques have shown high capacity in assessing the quality of agro-food commodities. Some of these methods can be used with high precision to monitor the quality attributes of agricultural and food commodities. This is achieved by an effective combination of sensors, mathematical models and algorithms to determine the relationships which exist between the quality traits of the commodity and the observed physical or chemical properties of the commodity (Ruiz-Altisent et al., 2010). Spectroscopy and imaging are two major optical techniques that have found application in quality and safety inspection of agricultural and food commodities (Du and Sun, 2004; Kumar and Mittal, 2010; Mizrach et al., 2009; Pallottino et al., 2010; Schlüter et al., 2009; Shankar et al., 2010; Singh et al., 2010).

Spectral imaging techniques acquire thousands of spectra per sample. A recent development includes hyperspectral, multispectral and laser light backscattering imaging. Based on the light source and the imaging unit used, the technique is divided into three categories, namely laser light (monochromatic) backscattering imaging (LLBI), multispectral backscattering imaging (MBI) and hyperspectral backscattering imaging (HBI). The images acquired by these categories are similar when a certain wavelength is selected (Mollazade et al., 2012). Therefore, this paper discusses different backscattering imaging technologies with emphasis on the application of emerging technologies i.e. LLBI, MBI and HBI.

2. Concept of light backscattering imaging

An object or a body may be transparent, semi-transparent or opaque in terms of the passage of light through it. Agricultural and food commodities are presumed to be semi-transparent or opaque and allow the passage of light at specific wavelengths (Mireei et al., 2010). Absorption, transmittance and reflectance may take place when light photons, or electromagnetic radiation, moves within a semi-transparent or opaque biological system (Qin, 2007). Light reflectance is an intricate phenomenon and can be looked at as steady (specular) reflectance, external diffuse reflectance, and scattering. Light reflection from a polished and smooth surface is called steady (specular) reflectance. The law of reflection proposes that the angle of incidence of light with the surface of a body is equal to the angle at which it is reflected, while external diffuse reflectance takes place at a fixed angle of 45° to the incident beam. This reflectance conveys certain information about the surface of the object such as colour and texture (Mireei et al., 2010).

Birth (1976) reported that for agricultural products, only 4%–5% of incident light is reflected by both steady (specular) and external diffuse reflectance. The rest of the light is transmitted through the skin tissue and is scattered through the permeable tissue of the internal components of the fruit or vegetable. The majority of the light travelling through the tissue is reflected by the internal components of the biological material and is dispersed towards the external tissue surface. As the backscattered photons have inherently interacted with the internal components of the tissue, these photons may provide some information about the structures and morphology of the tissues, and their mechanical properties etc. (Mollazade et al., 2012) as well as the water content (Romano et al., 2011; Hashim et al., 2013).

Scattering is a natural phenomenon of light that is related to cell size and the inter- and extra-cellular properties of the tissue matrices (Lu, 2004). Photons penetrating the surface will be initially refracted, obeying Snellius' law, i.e. photons entering a body with a higher refractive index are refracted towards the vertical axis to the surface (Steiner, 2011). Mathematically Snellius' law states:

$$\frac{Sin\theta_i}{Sin\theta_r} = n \tag{1}$$

where n is the refractive index, and θ_i and θ_r are the incident and refraction angles respectively.

Inside the object, the photons may undergo scattering. That is, they experience a change in direction of movement according to a probability function expressed as the anisotropy factor, g, or absorption, meaning the excitation of the absorbing molecule by an electronic transition such as the Henyey-Greenstein phase function which is given as:

$$P(\cos\theta) = \frac{1}{2}\frac{1-g^2}{\left(1+g^2-2g\cos\theta\right)^{3/2}} \tag{2}$$

where g is the anisotropy factor (0–1) and θ is the polar scattering.

When $g = 0$, this represents isotropic scattering and when $g = 1$, this represents forward scattering. The Henyey–Greenstein phase function simulates scattering functions which have been observed experimentally in biological tissue (Henyey and Greenstein, 1941; Jacques, 1998). McGlone et al. (1998) stated that the cell wall surfaces are the most predominant cause of the backscattering phenomenon because they give rise to abrupt changes in the refractive index within fruit and vegetables. Tissue starch, chloroplasts, and mitochondria are also responsible for scattering as a result of refraction at their surfaces (Nicolaï et al., 2007). The structural components of agricultural and food commodities can take up a particular amount of light. Photon absorption or scattering is a function of the types of structural components of the product, the light wavelength, and light path length. Therefore, light absorption and scattering properties can be used to group biological tissues since light absorption and scattering properties are material specific (Mireei et al., 2010).

HBI provides a substantial amount of information concerning the physical and chemical composition of an imaged object. Schaepman (2007) defined HBI as the simultaneous acquisition of spatial images in many spectrally contiguous bands measured from a remotely operated platform. HBI consists of both hardware and software, although the specific configuration may differ based on the object to be evaluated and the method of image acquisition. The common basic components of HBI include an illumination source to provide light, a detector which simultaneously acquires spectral and spatial resolution, a spectrograph, an objective lens, an objective table fixed to a conveyor belt to hold and convey the samples and a computer to create and store the acquired images (Fig. 1). An example of the acquired images is shown in Fig. 2. In contrast, MBI systems usually record less than ten bands. Therefore, they do not render a real spectrum in every image pixel (Ariana and Lu, 2010).

A LLBI system mainly comprises of a charge-coupled device (CCD) camera, a few laser diodes of different wavelengths which can be used interchangeably as a light source, as well as a computer to operate the camera and to capture the images, and store the data. After light has penetrated the object, the camera records a fraction of the backscattered light and transfers the data to the computer. An example of a LLBI image is shown in Fig. 3a, while the image profiles are shown in Fig. 3b and c. It can be seen that the intensity of the light decreases as the radius of the light spot increases. These

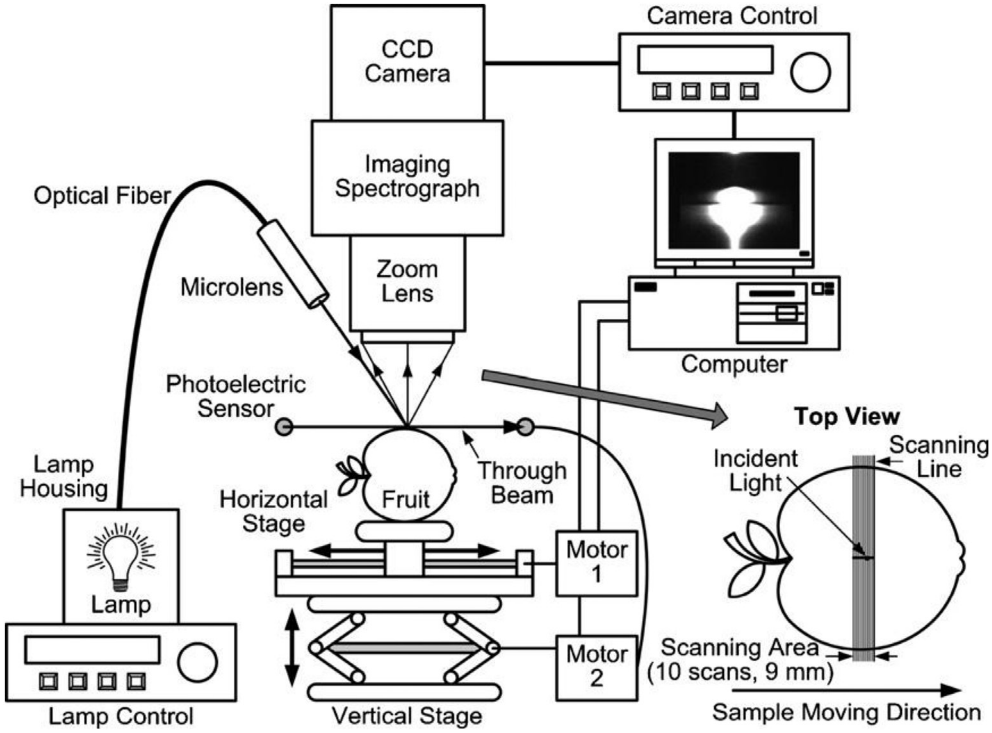

Fig. 1. Hyperspectral imaging system for acquiring spatially resolved scattering images from a fruit sample (Qin and Lu, 2008).

changes can be related to the interaction of the light with the quality attributes of agricultural and food commodities.

The application of backscattering imaging has been tested on several temperate crops such as tomatoes, apples and plums as well as some vegetables and foods. A summary of applications of backscattering imaging for agricultural and food products is as shown in Table 1.

3. Potential of backscattering imaging in agricultural and food processing

3.1. Applications of laser light backscattering imaging (LLBI)

It is known from studies that LLBI has been used to determine soluble solids content (SSC) and firmness. SSC and firmness have been linked with maturity or the level of ripeness and the shelf life of fruits and vegetables. SSC is known to increase as maturity progresses while flesh firmness in fruit decreases with increasing maturity. Various researchers have used LLBI to predict SSC and firmness in fruits and vegetables (Qing et al., 2008; Tu et al., 2006, 2000) and the outcome from these works has been remarkable. For example Qing et al. (2008) applied LLBI to assess the soluble solids content (SSC) and firmness of apples grown in different locations and at different stages of development. In the study, spectral images of Elstar and Pinova apples were captured with laser diodes emitting at five wavelengths (680, 780, 880, 940, and 980 nm) with a 10 nm bandpass, to assess fruit absorption and scattering properties. Different multivariate calibrations including partial least square regression (PLSR), stepwise multi-linear regression (SMLR), and principal component regression (PCR) were used as statistical analysis methods. The result revealed that a prediction of SSC and firmness of apples at different developmental stages and environmental growing conditions can be achieved using the five wavelengths. There was a positive correlation between SSC and the

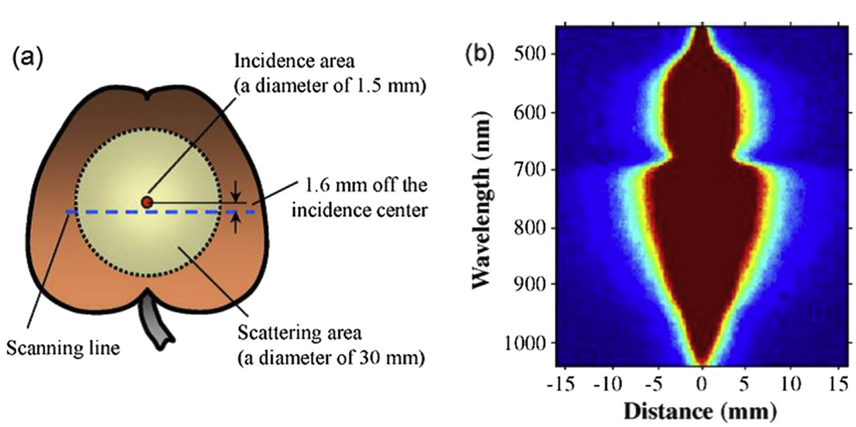

Fig. 2. (a) Scanning line and scattering area; (b) Raw hyperspectral scattering image (Peng and Lu, 2008).

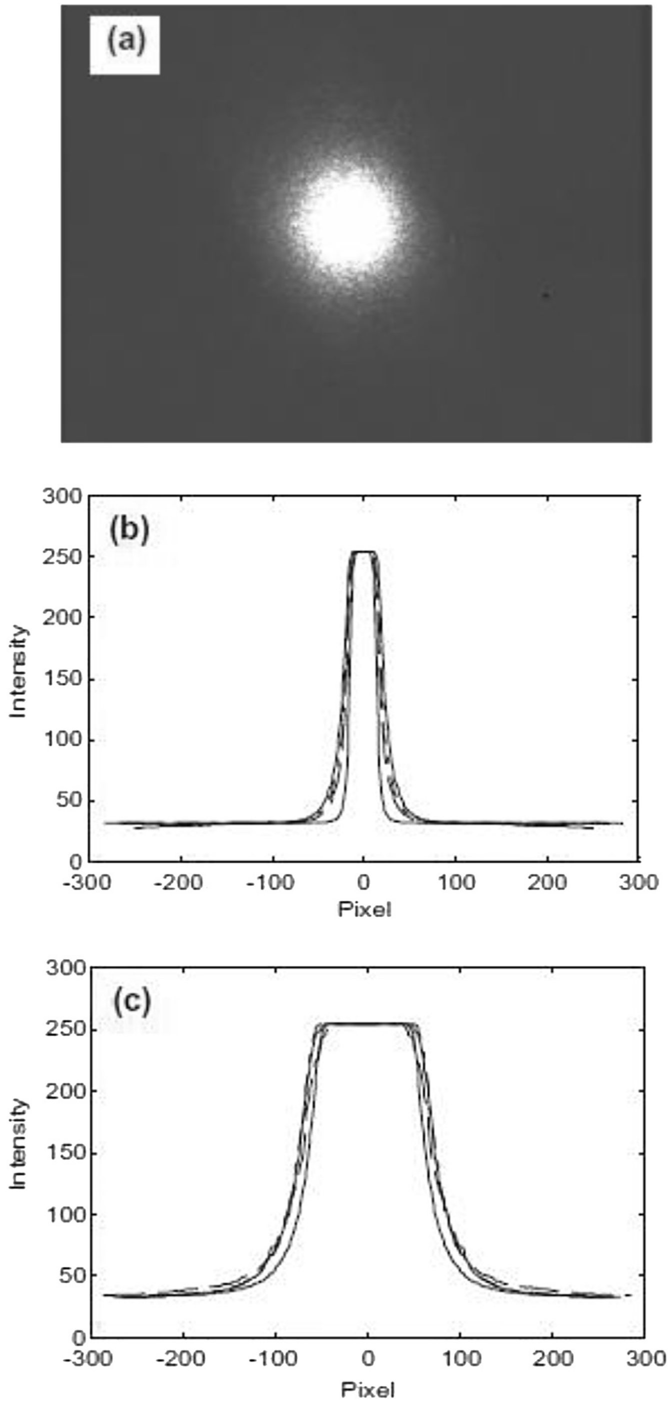

Fig. 3. Typical backscattering image and profiles of banana before storage (a) raw backscattering image (b) backscattering profile at 660 nm (c) backscattering profile at 785 nm (Hashim et al., 2013).

frequency of intensities, while a negative correlation was noticed between flesh firmness and frequency of intensities which was used to predict SSC and firmness of the apples. With correlation coefficient (R) values of 0.83 for SSC and 0.87 for firmness, it showed satisfactory prediction accuracy.

LLBI has also been used to monitor changes in drying parameters in fruits such as apple and banana (Romano et al., 2008, 2011). Moisture content, which is one of the major factors that determine shelf-life, must be carefully monitored to achieve effective drying. It has been reported that at lower temperatures there is a better correlation between backscattering parameters and moisture content. Romano et al. (2008) investigated the use of a LLBI system to monitor the changes in banana slices during drying. In their study, a 670 nm wavelength laser diode was employed as a light source and a CCD camera as a detector. The size of the total illuminated area in square centimetres and the radius in centimetres were measured to determine photon migration into the tissue. The banana samples were skinned and cut into slices of 2.5–3.0 cm diameter with 1.0–1.3 cm thickness. The slices were weighed and oven dried in a standard oven using three different temperatures (53 °C, 58 °C and 63 °C). Backscattering images of the banana slices were taken every hour during the drying process. The authors found that there was a selective response of two parameters, namely the area and radius of the intensity profile to the changes in moisture content. The LLBI parameters and the moisture content at the lowest temperature (53 °C) showed high correlations ($R^2 = 0.85$) between the normalised values and the classification results. The movement of the radius located by the inflection point migrating closer to the incident point with the decrease in the moisture content as drying time and temperature increased.

LLBI has further been used to determine defects in fruits and vegetables such as rot in citrus and chilling injury in banana (Hashim et al., 2013; Lorente et al., 2013). Defects in fruits and vegetables have been reported as not only reducing their market value, but also resulted in total rejection by consumers and consequently gave rise to greater waste. Therefore early detection of defects in fruits and vegetables is highly desirable. For instance, Lorente et al. (2013) investigated the detection of rot in citrus by five laser diodes which emitted light from visible to the near infrared range. Half of the samples were inoculated with spores of the fungus *Penicillium digitatum* and the other half were inoculated with water to serve as control samples. Five images were obtained from each fruit giving a total of 500 images for the whole study set. The Gaussian–Lorentzian (GL) function was used to describe the backscattering profiles since the images obtained had radial symmetry regarding the incidence point of the laser light. Linear discriminant analysis (LDA) was used as a classification model and the study achieved 80.4% detection accuracy at 532 nm while combinations of five wavelengths gave 96.1% detection accuracy. With an average coefficient of determination R^2 of 0.998, it shows that LLBI could be an efficient means to detect and predict defects in fruit and vegetables.

LLBI has been applied in the determination of the mechanical properties of some horticultural crops such as apple, plum, tomato and mushroom (Mollazade et al., 2013). Mechanical properties such as elastic modulus and firmness are influenced by maturity and time of harvest. They also aid in the evaluation and grading of fruits and vegetables. Mollazade et al. (2013) investigated the feasibility of texture-based models and the coefficients from space-domain analysis of LLBI to develop models for predicting the mechanical properties (firmness or elastic modulus) of several horticultural crops. In the study, 127 images of apples, 350 images of plums, 200 images of tomatoes and 200 images of mushrooms were acquired using laser light at 660 nm. A calibration model to predict firmness and elasticity of the horticultural crops studied were developed using an adaptive neuro-fuzzy inference system for real time applications. For such real time applications, the study revealed that 0.5 s or less was required for the processing time to run the algorithms including the first order statistics of the image histogram (FOSH), grey level co-occurrence matrix (GLCM), local binary pattern (LBP), wavelet and simultaneous autoregressive (SAR) statistical and texture-based techniques. Likewise 0.5 s or less was the time required to run the Lorentzian Distribution (LD), Gompertz Distribution (GD) and Farrell diffusion models. The models based

Table 1
A summary of applications of backscattering imaging for agricultural and food products.

Imaging technique	Wavelength (nm)	Material	Calibration model	Application	Reference
LLBI	660 and 785	Banana	SMLR	Chilling injury in bananas	Hashim et al., 2013
LLBI	660	Apple, plum, tomato and mushroom	ANFIS	Firmness and elastic modulus of apple, plum, tomato and mushroom	Mollazade et al., 2013
MBI	532, 635, 650, 780, 808, 850, 1064	Banana		Predicting pre-treatment effect on drying of banana discs	Denes et al., 2013
LLBI	532, 660, 785, 830, 1060	Citrus		Early detection of decay in citrus	Lorente et al., 2013
HBI	400–1000	Banana	MLR	Determination of quality and maturity at three drying temperatures	Rajkumar et al., 2012
LLBI	532 and 635	Bell pepper	NR	Prediction of MC and colour	Romano et al., 2011a
LLBI	635	Apple (Gala)	LR and PR	Prediction of MC, SSC and hardness during drying	Romano et al., 2011b
LLBI	670	Banana		Prediction of MC during drying	Romano et al., 2010
HBI	400–1000	Apple	ANN	Detecting chilling injury	ElMasry et al., 2009
LLBI	785	Apple (Pinova and Elstar)		Ripeness detection during storage	Baranyi et al., 2009
HBI	400–1000	Tomato		Ripeness detection	Qin and Lu 2008
LLBI	670 and 785	Apple (Idared and Golden Delicious		Bruise detection	Baranyai and Zude 2008
LLBI	680, 780, 880, 940 and 980	Apple (Elstar and Pinova	PLSR, PCR and SMLR	Prediction of firmness and SSC during ripening	Qing et al., 2008
LLBI	670	Banana	LR	Prediction of MC during drying process	Romano et al., 2008
HBI	496–1036	Beef meat	MLR	Prediction of tenderness	Cluff et al., 2008
LLBI	408	Apple (Golden delicious)	ANN	Prediction of skin and flesh colour, SSC, firmness and TA after storage	Noh and Lu, 2007
HBI	530–900	Milk	LR	Prediction of fat content	Qin and Lu, 2007
LLBI	650	Apple (Fuji and Gala)	LR	Ripeness detection during shelf life	Tu et al., 2006
HBI	500–1000	Peach (Red Haven and Coral Star	MLR	Prediction of firmness during ripening	Lu and Peng, 2006
HBI	530–950	Apple (Golden Delicious	MLR	Prediction of firmness and SSC after storage	Lu et al., 2006
MBI	650, 680, 700, 740, 800, 820, 880, 910, 990	Apple (Red and Golden Delicious)	MLR	Prediction of firmness during ripening	Peng and Lu, 2006
MBI	680, 880, 905, 940, 1060	Apple (Red Delicious)	ANN	Prediction of firmness and SSC after storage	Lu 2004
LLBI	670	Tomato	PR	Maturity evaluation	Tu et al., 2000

HBI, hyperspectral light backscattering imaging; MBI, multispectral light backscattering imaging; LLBI, laser light backscattering imaging; ANFIS, adaptive neuro fussy inference system; PR, polynomial regression; ANN, artificial neural network; LR, linear regression; MLR, multiple linear regression; PCR, principal component regression; NR, nonlinear regression; SMLR, stepwise multilinear regression; PLSR, partial least square regression; SSC, soluble solids content; TA, titratable acidity.

on the fusion of selected feature sets of texture analysis and space domain techniques managed to achieve a good prediction ability for the mechanical properties with R values of 0.896, 0.919, 0.790 and 0.887 for mushroom, tomato, plum and apple respectively. The combinations of space domain and texture-based features resulted in improved prediction accuracy of the mechanical properties.

In addition, LLBI has been used to determine the optical properties of fruits and vegetables (Baranyai et al., 2009; Baranyai and Zude, 2009; Do Trong et al., 2014). Optical properties have been compared with maturity level and sugar content. Changes in the optical properties of fruit tissue during the development and ripening stages can better aid the grading process. Baranyai et al. (2009) applied LLBI to determine the optical properties of apple tissue in cold storage. In the study, two apple cultivars ('Elstar' and 'Pinova') at unripe, ripe and overripe stages were each kept in separate chambers under a controlled atmosphere (2% CO_2, 1.5% O_2). Radial averaging was used to compute the backscattering profiles that were extracted from the captured backscattering images. The anisotropy factor (g), absorption coefficient (μ_a) and scattering coefficient (μ_s) were estimated from the analysis. The results indicated the total interaction coefficient (μ_t) (total distribution of light comprising absorption and scattering) was affected not only by flesh firmness but also by other fruit attributes. It also revealed that the estimated values of the optical properties of apple were strongly affected by storage time and apple cultivar.

3.2. Applications of multispectral light backscattering imaging (MBI)

Similar to LLBI, the application of MBI has been conducted on various types of agricultural produce in order to determine various quality attributes in fruits such as apple, peach, etc. (Lleó et al., 2009; Lu, 2004; Peng and Lu, 2005, 2006, 2007). Lu (2004) examined the use of MBI to predict firmness and SSC in apples. In total, about 550 apples were used in the study and spectral images of apple samples were captured using five wavelength bands i.e. 680, 880, 905, 940 and 1060 nm. Prior to measurement, the samples were stored for 5–6 months in a controlled environment at 2 ± 1 °C temperature and 93%–98% relative humidity to retain the pre-storage quality of the fruit. The samples were later refrigerated at 5 °C for four weeks and then transferred to a holding area at room temperature (24 °C) for a minimum of 15 h before the measurements were carried out. The ratios of the scattering profiles of the spectral images at each wavelength were used as input in back-propagation neural network models employed in the study for predicting the SSC and fruit firmness. The study found that four wavelengths with three ratio combinations i.e. F1/F4, F2/F3 and F3/F4 produced the best prediction of firmness with R being equal to 0.87 and a standard error of prediction of 5.8 N. On the other hand, three wavelengths with two ratio combinations i.e. F2/F3 and F3/F4 were sufficient to predict the SSC values. The authors found that the neural network prediction model for firmness compared well with other reported works from previous studies using NIR and other laser imaging techniques, but SSC prediction was not as good as other reported works using similar imaging techniques.

The application of MBI to predict drying parameters has been tested on banana. For instance, Dénes et al. (2013) studied the influence of antioxidant solution, drying temperature and the drying time of banana discs on MBI parameters. Laser diodes that emitted light from 532 nm to 1064 nm were used in this study. Banana discs of 10 mm thickness were treated with different antioxidant solutions of ascorbic acid to inhibit banana disc discolouration while drying. The treated discs were subjected to 50 °C and 80 °C drying temperatures and 6 h and 8 h drying time. Radial profiles were used to evaluate the light penetration pattern. Backscattering parameters of distance of inflection point (DIP), slope of logarithmic decay (SLD) and FWHM were compared with a normalised difference vegetation index (NDVI), which was used as a reference. The authors concluded that backscattering profiles of 532, 635 and 650 nm sensitively responded to the adjusted drying parameters of temperature and time, which resulted in less photon scattering being observed by intensity decay for movement close to the incident point. The result showed that the system can be used to monitor changes in the parameters during drying.

3.3. Applications of hyperspectral light backscattering imaging

In addition to the application of LLBI and MBI in the determination of agricultural and food commodity quality attributes, HBI has also found application in the determination of the quality attributes of fruits and vegetables. HBI has been used to determine quality attributes in apple, peach, cucumber, pear, kiwifruit, tomato etc. (Lu and Peng, 2006; Lu et al., 2006; Noh and Lu, 2007; Qin and Lu, 2008). For example, Qin and Lu (2008) employed a HBI system to estimate the optical properties of selected fruits and vegetables. In the study, a spatially resolved steady state diffuse reflectance technique with a visible and short-wave near-infrared wavelength between 500 and 1000 nm was used. A HBI system using an in-line scan mode was applied to capture spatially resolved diffuse reflectance images from eight samples each of three cultivars of apple (Golden Delicious, Red Delicious and Fuji) cucumber, pear, peach, plum, kiwifruit, zucchini squash, and tomato at three different stages of ripeness. An inverse algorithm for a diffusion theory model was used to determine the absorption and reduced scattering coefficients of the samples from the spatially resolved scattering profiles. The authors observed that water and major pigments such as chlorophylls, carotenoids or anthocyanins in the samples had a significant effect on the spectra of the absorption coefficient, while there was a decrease in the spectra of the reduced scattering coefficient with increasing wavelength. There was a wide variation in the values of absorption and reduced scattering coefficients among the samples tested. Tomatoes at the three different ripening stages (green, pink and red) showed large absorption spectra differences and the ratio of the absorption coefficient at 675 nm for chlorophyll to that at 535 nm for lycopene was used to classify the samples into different stages of ripeness. It was noted that major pigments of the plant tissue such as chlorophyll, carotene and carotenoid had a significant effect on the penetration depth of light.

HBI has also been used to detect defects in fruits such as apple (ElMasry et al., 2009, 2008). For example, ElMasry et al. (2009) applied HBI to detect chilling injury in 'Red Delicious' apples. In the study, an established HBI system operating at wavelengths of 400–1000 nm was employed to capture, pre-process and extract the spectral properties of 'Red Delicious' apples as shown in Fig. 4. Sixty-four Red Delicious apples free from defects, bruises, disease and contamination were picked for the experiment. A chilling injury was induced in 32 apples by storing at −1 °C for 24 h. After that they were removed from the cold storage and kept at room temperature (20 ± 1 °C) for another 24 h to facilitate the proper development of the chilling injury symptoms. The remaining 32 apples which served as control samples were kept at room temperature (20 ± 1 °C). An artificial neural network (ANN) was used as a calibration model for the classification and firmness prediction of normal and injured Red Delicious apples. The work recorded 98.4% classification accuracy in the detection of normal and injured 'Red Delicious' apples.

4. Analysis of backscattering images

The most important step in the application of a backscattering imaging system is to find the appropriate wavelength for assessing the optical property of interest. The reason is that there are variations in the structures of the objects being investigated and these variations correspond to different optical properties. Therefore a specific wavelength is required to determine the selected properties. To overcome this, several researchers have recommended several wavelength ranges. Some have suggested the appropriate wavelengths for measurement of fruit quality were in the range of visible light to NIR (400–1000). The 620, 880, 940 and 1010 nm wavelengths have been used to determine the SSC of cherries, apples and apricots (Carlini et al., 2000; Qing et al., 2007; Ventura et al., 1998). Other researchers have suggested 680, 860 and 800–1100 nm as appropriate wavelengths for the detection of firmness in apples, kiwifruits and plums (McGlone et al., 1998; Moons et al., 1998; Paz et al., 2008; Qing et al., 2007). Qing et al. (2007) further suggested 910 nm as an appropriate wavelength to determine moisture content.

In backscattering imaging, the beam size used in the imaging system is of significant importance. Lu (2004) noted that although a large beam size offers better light distribution, it may lead to problems in scattering quantification as photons do not travel along the same path lengths. For a smaller beam size, scattering quantification is straightforward but the efficiency of the lighting system is greatly reduced, leading to a smaller scattering area due to the detecting device receiving fewer photons. There is a need to carefully select the beam size in order to obtain an accurate result from the image capturing device. The choice of beam size is also important in order to reduce or avoid pixel saturation, which has a direct correlation with scattering area.

Another important consideration in a backscattering imaging system is the incident angle of the light beam. Various researchers have used different incident angles in their work such as 21° (Lu, 2004) and 15° (Hashim et al., 2013; Mollazade et al., 2013). This is to avoid oversaturation of the photons, and also to prevent direct reflection back to the camera. The positioning of the incident angle of the light beam allows for ease of processing of the images. When the incident angle of the light beam is carefully selected, it aids the image to be symmetrical about the incident point.

After image acquisition, the acquired images are segmented and pre-processed to remove noise and all irrelevant information in the raw data before being analysed using statistical analysis. Various researchers have developed diverse algorithms to process backscattering images and a number of methods have been proposed for describing the image texture (Zheng et al., 2006). These include statistical, structural, model-based and transform-based texture analysis as shown in Fig. 5. Haralick et al. (1973) reported that the most frequently used statistical textural analysis technique is the Grey-Level Co-Occurrence Matrix (GLCM), which is based on the use of second order statistics of the grayscale image histograms. The space-frequency decomposition ability has made the Gabor or

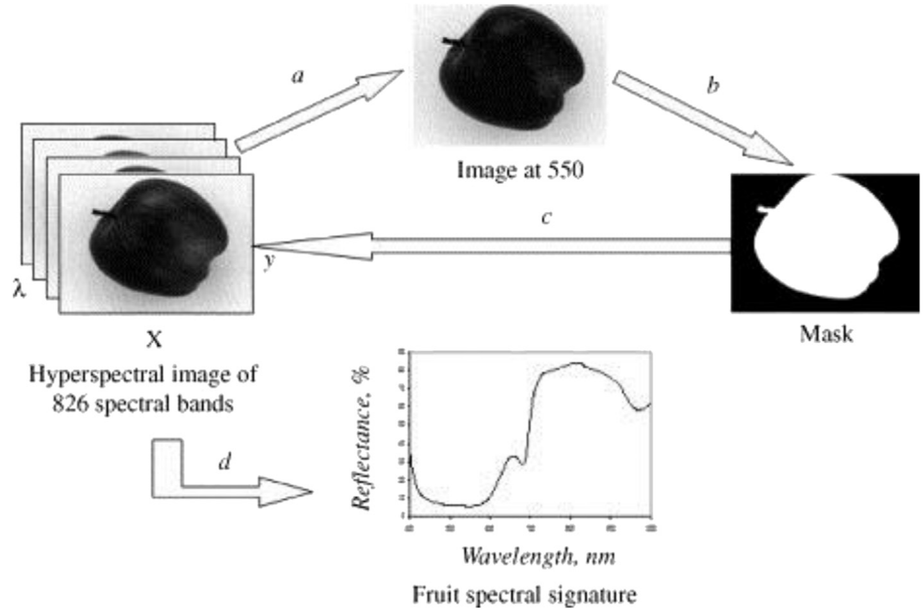

Fig. 4. Extraction of the fruit spectral signature: (a) selecting 550 nm image, (b) binarization (defining the AOI); (c) applying the mask; and (d) calculating the fruit spectral signature using only those at the white pixels in the mask (ElMasry et al., 2009).

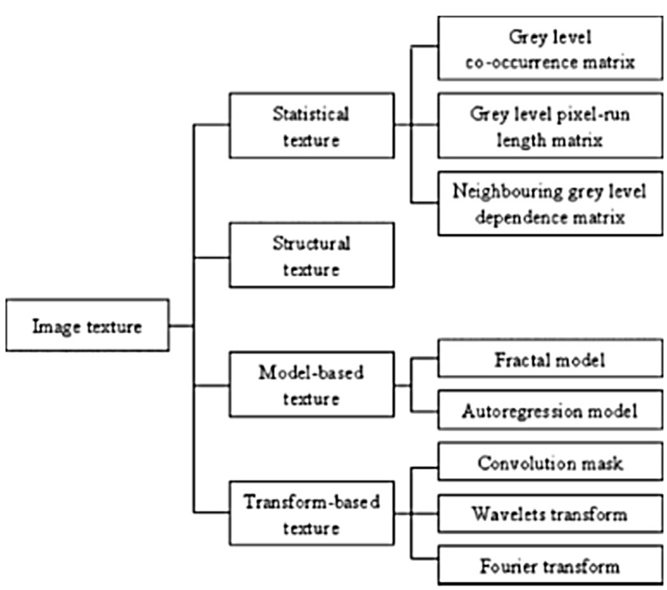

Fig. 5. Overview of texture analysis methods (Zheng et al., 2006).

wavelet transform a preferred choice among transform-based texture analysis techniques. The wavelet transform method has been used both for feature extraction and texture characterisation. It also has been used to address the problems of segmentation and classification (Chang and Kuo, 1993; Laine and Fan, 1996; Unser, 1995).

Since the large dimensions of textural features are usually extracted from backscattering profiles, it is very difficult to derive any meaningful relationship from the extracted textural features and the quality parameters that are intended to be evaluated. Thus, the extracted features are not directly used to determine quality parameters. The majority of the feature extraction methods currently employed in light backscattering imaging tend to focus on fitting mathematical functions or models to one-dimensional scattering profiles. Subsequently, the parameters obtained from these functions or models are used as features. Mollazade et al. (2012) suggested that since laser light backscattering imaging provides two-dimensional images with pixel intensity values of different patterns, extracting texture features of such images could result in a better prediction of the qualitative parameters of agricultural and food commodities.

Although pre-processing is important in image processing, if not properly done then this process offers uncertainties concerning the accuracy of the results. For example, the techniques of radial and profile averaging result in a profound reduction of the backscattering data (Lu, 2004; Peng and Lu, 2006) while spectral averaging over a sequential series of wavelengths increased processing time (Mollazade et al., 2012). These could be limitations for a real-time application. Also, there is considerable loss in image resolution when the pixel binning technique is used. These highlighted reductions in the data size of backscattered images may negatively affect the final results of LLBI systems (Mollazade et al., 2012).

The success of any segmentation procedure is usually determined by correct pre-processing of the images (Blasco et al., 2007). Lu (2004) suggested Principal Component Analysis (PCA) or Partial Least Square regression (PLS) be used to pre-process the profile data. The advantages of PLS are that it can remove noise from the original data, reduce the dimensionality of the input data and reduce the risk of overfitting based on the training data. Peng and Lu (2006) adopted a filtering method to remove isolated spots on the scattering profile data and the results showed better firmness prediction with the best correlation, $R = 0.854$ when 18% low grayscale pixels were removed. The classical thresholding technique i.e. Bimodal and Otsu's thresholding methods are widely used for image segmentation processing. Pedrycz et al. (1998) reported that the performance of these methods is usually reduced in images with unfavourably defined regions. Mollazade et al. (2012) suggested the use of fuzzy set models as a way to incorporate the uncertainty to obtain an improvement in the thresholding. The fuzzy set method is a set theory that models reality when an empirical validation is desired (Zimmermann, 1980). It is a modelling, problem solving and data mining tool which has proven

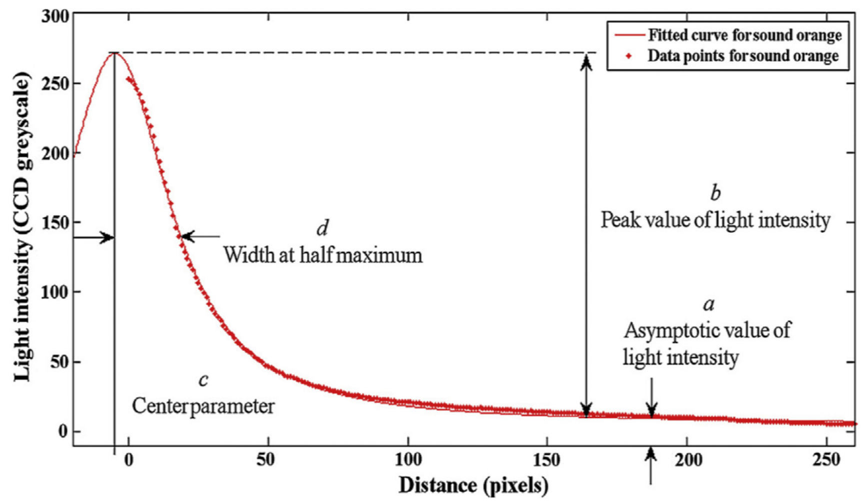

Fig. 6. Gaussian–Lorentzian cross product distribution model for backscattering profiles (Lorente et al., 2013).

to be superior to existing methods in many cases (Zimmermann, 2010).

The segmented backscattering images can be analysed using different methods such as optical scattering (Cluff et al., 2008), changes in light intensity (Hashim et al., 2013; Romano et al., 2011) and radial averaging (Peng and Lu, 2006, 2008). These produce a backscattering profile which can be fitted to mathematical models such as LD (Eq. (3)), MLD (Eq. (4)) and GL (Eq. (5)) functions.

$$I_{wi} = \frac{a_{wi}}{1 + \left(\frac{x}{b_{wi}}\right)^2} \tag{3}$$

where I is the light intensity in the CCD count, x is the scattering distance measured from the beam incident centre in mm, a is peak value of the scattering profile at $x = 0$ in the CCD count value in mm, b is the full width of the scattering profile at one half of the peak value in mm and wi is a specific wavelength with $i = 1, 2, 3, \ldots$ N, where N is the total number of wavelengths.

$$R = \frac{b}{(1 + x/c)^d} \tag{4}$$

where R is a Modified Lorentzian Distribution function, b is the peak value of the profile, c is the FWHM, d is the slope around the FWHM and x is the scattering distance.

$$I(x) = a + \frac{b}{\left[1 + e\left(\frac{x-c}{d^2}\right)\exp((1-e)/2)(x-c)/d\right)^2\right]} \tag{5}$$

where I is the light intensity of each circular band after radial averaging, x is the scattering distance expressed as the number of pixels, a is the asymptotic value of the light intensity when x approaches infinity, b is the peak value of the estimated light intensity at the centre, c is the centre parameter, d is the full scattering width that produces the half maximum peak value, and e relates to the shape of the backscattering images.

An example of a GL cross product distribution of backscattering profiles is as shown in Fig. 6. From the fitted profile, other parameters can be obtained such as the Inflection Point (IP) and Saturation Radius (Rsat). The FWHM, IP and Rsat were used to assess the level of chilling injury in banana (Hashim et al., 2013), tenderness in beef steak (Cluff et al., 2008), tissue changes in kiwifruit, bananas and apples (Romano et al., 2008).

In terms of statistical analysis, most researchers have developed calibration models to predict the quality of produce. The calibration models that have been used in backscattering imaging were developed using multivariate analysis such as multi-regression, ANN, linear discriminant analysis (LDA), PLS etc. Multi-regression analysis has been used to predict chilling injury in bananas (Hashim et al., 2013), firmness (Peng and Lu, 2006) and SSC in apples (Peng and Lu, 2008) while ANN has been used to develop calibration models to predict the sugar content in potatoes (Rady et al., 2015), detect chilling injury in apples (ElMasry et al., 2009), predict apple firmness and SSC (Lu, 2004) and determine the mechanical properties of horticultural crops (Mollazade et al., 2013). LDA has successfully classified banana slices according to drying time (Romano et al., 2008) and detected decay in citrus (Lorente et al., 2013). Further, PLS has been used to detect bruises (ElMasry et al., 2008) and predict the maturity of freshly harvested apples (Zude-Sasse et al., 2002). All these different analysis approaches show significant results and seemingly served as a bridge between the extracted features and the corresponding quality attributes (physical, physicochemical or mechanical properties).

5. Conclusion

In this review an attempt has been made to present an overview of various applications of hyperspectral, multispectral and laser light backscattering imaging of agricultural produce by numerous researchers who have worked on the subject matter. The review has highlighted the types of crops that have been measured, the selection of laser light wavelengths, the parameters used for prediction and the methods used for developing the calibration and prediction models. Much work has been done in the application of backscattering imaging to detect the internal characteristics of agricultural and food products such as moisture content, firmness, SSC, acidity and the presence of external defects. However, there are still some challenges which must be overcome for the effective deployment of the system. The main challenge is the ability to achieve real time and continuous assessment. Most published works have been conducted based on batch assessment which does not represent the real online sorting and grading situation which is necessary to evaluate a high number of products per unit time.

More work is needed in the area of image processing algorithms in order to improve processing and analysis time per image.

Nevertheless, backscattering imaging demonstrates a high potential to provide a non-destructive low-cost technology with rapid evaluation for predicting the quality of agricultural and food commodities. All the fundamental studies have shown promising results indicating the effectiveness of the method as a new tool for assessment of quality.

Acknowledgement

The authors are grateful for the financial support received from the Ministry of Science, Technology and Innovation, Malaysia under a Science Fund research grant (Vot number: 5450728).

References

Ariana, D.P., Lu, R., 2010. Evaluation of internal defect and surface color of whole pickles using hyperspectral imaging. J. Food Eng. 96 (4), 583–590.

Baranyai, L., Regen, C., Zude, M., 2009. Monitoring optical properties of apple tissue during cool storage. In: Proceedings of CIGR Workshop on Image Analyses in Agriculture. BAB, pp. 112–119.

Baranyai, L., Zude, M., 2009. Analysis of laser light propagation in kiwifruit using backscattering imaging and Monte Carlo simulation. Comput. Electron. Agric. 69 (1), 33–39.

Blasco, J., Aleixos, N., Moltó, E., 2007. Computer vision detection of peel defects in citrus by means of a region oriented segmentation algorithm. J. Food Eng. 81 (3), 535–543.

Baranyai, L., Zude, M., 2008. Analysis of laser light migration in apple tissue by Monte Carlo simulation. Prog. Agric. Eng. Sci. 4 (1), 45–59.

Birth, G.S., 1976. How light interacts with foods. In: Gaffney Jr., J.J. (Ed.), Quality Detection in Foods. American Society for Agricultural Engineering, St. Joseph, MI, pp. 6–11.

Carlini, P., Massantini, R., Mencarelli, F., 2000. Vis-NIR measurement of soluble solids in cherry and apricot by PLS regression and wavelength selection. J. Agric. Food Chem. 48 (11), 5236–5242.

Chang, T., Kuo, C.-C., 1993. Texture analysis and classification with tree-structured wavelet transform. Image Process. IEEE Trans. 2 (4), 429–441.

Choi, K.-H., Lee, K.-J., Kim, G., 2006. Nondestructive quality evaluation technology for fruits and vegetables using near-infrared spectroscopy. In: International Seminar on Enhancing Export Competitiveness of Asian Fruits.

Cluff, K., Naganathan, G.-K., Subbiah, J., Lu, R., Calkins, G.-R., Samal, A., 2008. Optical scattering in beef steak to predict tenderness using hyperspectral imaging in the VIS-NIR region. Sens. Instrum. Food Qual. Saf. 2 (3), 189–196.

Dénes, L.D., Parrag, V., Felföldi, J., Baranyai, L., 2013. Influence of parameters of drying on laser induced diffuse reflectance of banana discs. J. Food Phys. 26 (1), 11–16.

Do Trong, N.N., Erkinbaev, C., Tsuta, M., De Baerdemaeker, J., Nicolaï, B., Saeys, W., 2014. Spatially resolved diffuse reflectance in the visible and near-infrared wavelength range for non-destructive quality assessment of 'Braeburn'apples. Postharvest Biol. Technol. 91, 39–48.

Du, C.-J., Sun, D.-W., 2004. Recent developments in the applications of image processing techniques for food quality evaluation. Trends Food Sci. Technol. 15 (5), 230–249.

ElMasry, G., Wang, N., Vigneault, C., 2009. Detecting chilling injury in Red Delicious apple using hyperspectral imaging and neural networks. Postharvest Biol. Technol. 52 (1), 1–8.

ElMasry, G., Wang, N., Vigneault, C., Qiao, J., ElSayed, A., 2008. Early detection of apple bruises on different background colors using hyperspectral imaging. LWT-Food Sci. Technol. 41 (2), 337–345.

Greensill, C., Newman, D., 1999. An investigation into the determination of the maturity of pawpaws (Carica papaya) from NIR transmission spectra. J. Near Infrared Spectrosc. 7 (2), 109–116.

Haralick, R.M., Shanmugam, K., Dinstein, I.H., 1973. Textural features for image classification. Systems, man and cybernetics. IEEE Trans. (6), 610–621.

Hashim, N., Pflanz, M., Regen, C., Janius, R.B., Abdul Rahman, R., Osman, A., Shitan, M., Zude, M., 2013. An approach for monitoring the chilling injury appearance in bananas by means of backscattering imaging. J. Food Eng. 116 (1), 28–36.

Henyey, L.G., Greenstein, J.L., 1941. Diffuse radiation in the galaxy. Astrophysical J. 93, 70–83.

Jacques, S.L., 1998. Light distributions from point, line and plane sources for photochemical reactions and fluorescence in turbid biological tissues. Photochem. Photobiol. 67 (1), 23–32.

Kumar, S., Mittal, G.S., 2010. Rapid detection of microorganisms using image processing parameters and neural network. Food Bioprocess Technol. 3 (5), 741–751.

Laine, A., Fan, J., 1996. Frame representations for texture segmentation. Image Process. IEEE Trans. 5 (5), 771–780.

Lleó, L., Barreiro, P., Ruiz-Altisent, M., Herrero, A., 2009. Multispectral images of peach related to firmness and maturity at harvest. J. Food Eng. 93 (2), 229–235.

Lorente, D., Zude, M., Regen, C., Palou, L., Gomez-Sanchis, J., Blasco, J., 2013. Early decay detection in citrus fruit using laser-light backscattering imaging. Postharvest Biol. Technol. 86, 424–430.

Lu, R., 2004. Multispectral imaging for predicting firmness and soluble solids content of apple fruit. Postharvest Biol. Technol. 31 (2), 147–157.

Lu, R., Peng, Y., 2006. Hyperspectral scattering for assessing peach fruit firmness. Biosyst. Eng. 93 (2), 161–171.

Lu, R., Qin, J., Peng, Y., 2006. Measurement of the optical properties of apples by hyperspectral imaging for assessing fruit quality. In: ASAE Annual International Meeting.

McGlone, V., Kawano, A., Kawano, S., 1998. Kiwifruit firmness by near infrared light scattering. J. Near Infrared Spectrosc. 5 (2), 83–89.

Mireei, S., Mohtasebi, S., Massudi, R., Refiee, S., Arabanian, A., 2010. Feasibility of near infrared spectroscopy for analysis of date fruits. Int. Agrophys. 24, 351–356.

Mizrach, A., Lu, R., Rubino, M., 2009. Gloss evaluation of curved-surface fruits and vegetables. Food Bioprocess Technol. 2 (3), 300–307.

Mollazade, K., Omid, M., Akhlaghian Tab, F., Kalaj, Y.R., Mohtasebi, S.S., Zude, M., 2013. Analysis of texture-based features for predicting mechanical properties of horticultural products by laser light backscattering imaging. Comput. Electron. Agric. 98, 34–45.

Mollazade, K., Omid, M., Tab, F.A., Mohtasebi, S.S., 2012. Principles and applications of light backscattering imaging in quality evaluation of agro-food products: a review. Food Bioprocess Technol. 5 (5), 1465–1485.

Moons, E., Sinnaeve, G., Dardenne, P., 1998. Non destructive visible and NIR spectroscopy measurement for the determination of apple internal quality. In: XXV International Horticultural Congress, Part 7: Quality of Horticultural Products 517, pp. 441–448.

Nicolaï, B.M., Beullens, K., Bobelyn, E., Peirs, A., Saeys, W., Theron, K.I., Lammertyn, J., 2007. Nondestructive measurement of fruit and vegetable quality by means of NIR spectroscopy: a review. Postharvest Biol. Technol. 46 (2), 99–118.

Noh, H.K., Lu, R., 2007. Hyperspectral laser-induced fluorescence imaging for assessing apple fruit quality. Postharvest Biol. Technol. 43 (2), 193–201.

Pallottino, F., Menesatti, P., Costa, C., Paglia, G., De Salvador, F.R., Lolletti, D., 2010. Image analysis techniques for automated hazelnut peeling determination. Food Bioprocess Technol. 3 (1), 155–159.

Paz, P., Sánchez, M.-T., Pérez-Marín, D., Guerrero, J.-E., Garrido-Varo, A., 2008. Nondestructive determination of total soluble solid content and firmness in plums using near-infrared reflectance spectroscopy. J. Agric. Food Chem. 56 (8), 2565–2570.

Pedrycz, W., Bonissone, P.P., Ruspini, E.H., 1998. Handbook of Fuzzy Computation. Institute of Physics Pub.

Peng, Y., Lu, R., 2005. Modeling multispectral scattering profiles for prediction of apple fruit firmness. Trans. Am. Soc. Agric. Eng. 48 (1), 235.

Peng, Y., Lu, R., 2006. Improving apple fruit firmness predictions by effective correction of multispectral scattering images. Postharvest Biol. Technol. 41 (3), 266–274.

Peng, Y., Lu, R., 2007. Prediction of apple fruit firmness and soluble solids content using characteristics of multispectral scattering images. J. Food Eng. 82 (2), 142–152.

Peng, Y., Lu, R., 2008. Analysis of spatially resolved hyperspectral scattering images for assessing apple fruit firmness and soluble solids content. Postharvest Biol. Technol. 48 (1), 52–62.

Qin, J., 2007. Measurement of the Optical Properties of Horticultural and Food Products by Hyperspectral Imaging, p. 68.

Qin, J., Lu, R., 2008. Measurement of the optical properties of fruits and vegetables using spatially resolved hyperspectral diffuse reflectance imaging technique. Postharvest Biol. Technol. 49 (3), 355–365.

Qing, Z., Ji, B., Zude, M., 2007. Wavelength selection for predicting physicochemical properties of apple fruit based on near-infrared spectroscopy. J. Food Qual. 30 (4), 511–526.

Qing, Z., Ji, B., Zude, M., 2008. Non-destructive analyses of apple quality parameters by means of laser-induced light backscattering imaging. Postharvest Biol. Technol. 48 (2), 215–222.

Qin, J., Lu, R., 2007. Measurement of the absorption and scattering properties of turbid liquid foods using hyperspectral imaging. Appl. Spectrosc. 61 (4), 388–396.

Rajkumar, P., Wang, N., Elmasry, G., Raghavan, G.S.V., Gariepy, Y., 2012. Studies on banana fruit quality and maturity stages using hyperspectral imaging. J. Food Eng. 108, 194–200.

Romano, G., Argyropoulos, D., Gottschalk, K., Cerruto, E., Müller, J., 2010. Influence of colour changes and moisture content during banana drying on laser backscattering. Int. J. Agric. Biol. Eng. 3, 46–51.

Rady, A., Guyer, D., Lu, R., 2015. Evaluation of sugar content of potatoes using hyperspectral imaging. Food Bioprocess Technol. 1–16.

Romano, G., Baranyai, L., Gottschalk, K., Zude, M., 2008. An approach for monitoring the moisture content changes of drying banana slices with laser light backscattering imaging. Food Bioprocess Technol. 1 (4), 410–414.

Romano, G., Nagle, M., Argyropoulos, D., Müller, J., 2011. Laser light backscattering to monitor moisture content, soluble solid content and hardness of apple tissue during drying. J. Food Eng. 104 (4), 657–662.

Ruiz-Altisent, M., Ruiz-Garcia, L., Moreda, G.P., Lu, R., Hernandez-Sanchez, N., Correa, E.C., Diezma, B., Nicolaï, B., Garcia-Ramos, J., 2010. Sensors for product

characterization and quality of specialty crops—a review. Comput. Electron. Agric. 74 (2), 176–194.
Schaepman, M.E., 2007. Spectrodirectional remote sensing: from pixels to processes. Int. J. Appl. Earth Obs. Geoinform. 9 (2), 204–223.
Schlüter, O., Foerster, J., Geyer, M., Knorr, D., Herppich, W.B., 2009. Characterization of high-hydrostatic-pressure effects on fresh produce using chlorophyll fluorescence image analysis. Food Bioprocess Technol. 2 (3), 291–299.
Shankar, T.J., Sokhansanj, S., Bandyopadhyay, S., Bawa, A., 2010. A case study on optimization of biomass flow during single-screw extrusion cooking using genetic algorithm (GA) and response surface method (RSM). Food Bioprocess Technol. 3 (4), 498–510.
Singh, C.B., Choudhary, R., Jayas, D.S., Paliwal, J., 2010. Wavelet analysis of signals in agriculture and food quality inspection. Food Bioprocess Technol. 3 (1), 2–12.
Singhal, R.S., Kulkarni, P., Reg, D., 1997. Handbook of Indices of Food Quality and Authenticity. Elsevier.
Steiner, R., 2011. Laser-tissue Interactions, Laser and IPL Technology in Dermatology and Aesthetic Medicine. Springer, pp. 23–36.
Tu, K., Chen, Y.Y., Ren, K., Shao, X.F., Dong, Q.L., Pan, L.Q., 2006. Modeling apple quality changes based on laser scattering image analysis under simulated shelf life conditions. Acta Hortic. 712, 371–380.
Tu, K., Jancsók, P., Nicolaï, B., De Baerdemaeker, J., 2000. Use of laser-scattering imaging to study tomato-fruit quality in relation to acoustic and compression measurements. Int. J. Food Sci. Technol. 35 (5), 503–510.
Unser, M., 1995. Texture classification and segmentation using wavelet frames. Image Process. IEEE Trans. 4 (11), 1549–1560.
Ventura, M., de Jager, A., de Putter, H., Roelofs, F.P., 1998. Non-destructive determination of soluble solids in apple fruit by near infrared spectroscopy (NIRS). Postharvest Biol. Technol. 14 (1), 21–27.
Zheng, C., Sun, D.-W., Zheng, L., 2006. Recent applications of image texture for evaluation of food qualities—a review. Trends Food Sci. Technol. 17 (3), 113–128.
Zimmermann, H.-J., 1980. Testability and meaning of mathematical models in social sciences. Math. Model. 1 (1), 123–139.
Zimmermann, H.J., 2010. Fuzzy Set Theory. Wiley Interdisciplinary Reviews: Computational Statistics, 2 (3), pp. 317–332.
Zude-Sasse, M., Truppel, I., Herold, B., 2002. An approach to non-destructive apple fruit chlorophyll determination. Postharvest Biol. Technol. 25 (2), 123–133.