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Imaging Technologies for Nondestructive Measurement of Internal Properties of Agricultural Products: A Review

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Abstract

Purpose: This study reviewed the major nondestructive measurement techniques used to assess internal properties of agricultural materials that significantly influence the quality, safety, and value of the products in markets. **Methods:** Imaging technologies are powerful nondestructive analytical tools that possess specific advantages in revealing the internal properties of products. **Results:** This review was exploring the application of various imaging techniques, specifically, hyperspectral imaging (HSI), magnetic resonance imaging (MRI), soft X-ray, X-ray computed tomography (XRI-CT), thermal imaging (TI), and ultrasound imaging (UI), to investigate the internal properties of agricultural commodities. **Conclusions:** The basic instruments used in these techniques are discussed in the initial part of the review. In the context of an investigation of the internal properties of agricultural products, including crops, fruits, vegetables, poultry, meat, fish, and seeds, various extant studies are examined to understand the potential of these imaging technologies. Future trends for these imaging techniques are also presented.

Keywords: Agricultural products, Hyperspectral imaging, Imaging technologies, Internal properties, Magnetic resonance imaging

Introduction

Food is the most important source of fundamental nutrients, including carbohydrates, fats, proteins, vitamins, and minerals, for the existence of human life. The basic origins of foods typically correspond to agricultural products that are classified as grains, animal feed, oilseeds, livestock, poultry, and dairy products. Examples include meats, eggs, fruits, and vegetables (Ruiz-Altisent and Moreda, 2011). Currently, most agricultural products used for consumption purposes are processed by various food industries. When we buy food from the market, we focus on purchasing the best quality of food because health issues are directly related to food consumption. Thus, significant social concern and global attention have been focused on food quality and its evaluation. Food quality implies the excellence of food in all the characteristics that are evaluated based on consumer requirements. External quality factors, such as size, shape, color, texture, and appearance, are perceived by the senses, including sight and touch, of the consumer. Taste and smell also help a consumer judge the quality of the food (Butz et al., 2005). It is quite difficult to evaluate internal quality properties, such as maturity, sugar content, acidity, oil content, internal defects, and tissue breakdowns, and more advanced technologies are required to obtain a better prediction of the internal quality.

Various steps, including handling, processing, sorting, and grading, are followed by the food industries to ensure the external and internal quality of their products, and this makes the process extremely complex and difficult.

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Chemical analytical evaluation and mechanical methods are commonly used to monitor the quality of food, as are human panel tests. Human panel tests are still used to evaluate the grades of tea, coffee, wine, and dairy products, and are time-consuming, subjective, and affected by adaptation, fatigue, and mental states (Yang et al., 2006). Chemical analytical measurement is performed as a means of quality management to determine the chemical composition and characteristics of agricultural products. The method provides important results, although it is only feasible in laboratories because the experiments require sophisticated instruments and preprocessed samples. Typically, this method is unable to provide real-time and online results, and this constitutes a significant barrier for a massive quality monitoring system. Mechanical and optical methods are used wherein the size, mass, and color correspond to the parameters for quality control of agricultural products. For example, Riyadi et al. (2007) developed a computer vision system for grading sizes of papaya, Khojastehnazhand et al. (2010) investigated a sorting system for lemons based on color and size, and Badhe et al. (2011) examined a computerized machine to grade mangos into five grades based on weight. These methods are only suitable for the evaluation of external quality. Thus, nondestructive and rapid measurement systems are necessary to investigate the internal properties of agricultural products.

Imaging technologies are very powerful nondestructive tools to monitor both external and internal properties of agricultural products. Over the past few decades, several studies have used imaging technologies, including one by Kamruzzaman et al. (2012) that involved the application of near-infrared (NIR) hyperspectral imaging (HIS) to determine the chemical composition of lamb meat. Kim and Schatzki (2001) successfully applied X-ray imaging (XRI) to detect pinholes in almonds. Additionally, MRI and X-ray CT were used by Lammertyn et al. (2003) to measure the internal core breakdown in pears. Manickavasagan et al. (2008) used thermal imaging (TI) technology to detect *Cryptolestes ferrugineus* inside wheat kernels. These studies focused on quality management wherein the results demonstrated the importance of imaging technologies. There is an increasing need for improvements in camera technologies and in the analysis and processing power of software and computers so that these technologies can be applied in various fields of quality monitoring.

It is especially critical to determine the internal properties of agricultural products, such as sugar content, acidity, oil content, and internal damage, that significantly influence the quality of the product. Hyperspectral imaging (HSI), MRI, XRI, X-ray computed tomography (X-ray CT), TI, and ultrasound imaging (UI) represent promising technologies for examining the internal properties of fruits, vegetables, and other agricultural products. These technologies are suitable for determining internal properties based on their own individual attributes. Specifically, HSI and MRI are well-suited to diagnose the chemical specifications of agricultural commodities because HSI spectra can identify the chemical bonds in the products and MRI measures magnetic properties, such as protons, which offer specific clues on the chemical compounds of a product (Mariette and Chimie, 2004; Aenugu et al., 2011). Soft X-rays and X-ray CT are very effective at identifying internal fractures in fruits or vegetables because they successfully image bones (Tao and Ibarra, 2000; Morita et al., 2003). The potential uses of TI in agriculture and food industries include the examination of the ripeness of fruits, bruise detection in fruits and vegetables, and detection of foreign bodies in food material (Vadivambal and Jayas, 2011). UI is an important alternative to X-rays for investigating the internal properties of agricultural materials (Cho and Irudayaraj, 2003).

Several researchers have reviewed imaging technologies with respect to food quality and safety control and presented the potential of imaging technologies. Chen and Sun (1991) reviewed a few nondestructive methods including imaging techniques, such as X-ray scanning, ultrasonic scanning, and nuclear magnetic resonance (NMR) imaging, for evaluating the quality of agricultural products. Image processing is one of the main tools for extracting information about the quality of a product. It involves several steps, including image acquisition, image segmentation, feature extraction, and classification, as investigated by Du and Sun (2004). Ruiz-Altisent et al. (2010) summarized a list of sensor technologies, including computer vision, spectroscopy, X-ray, magnetic resonance, chemical sensing, wireless sensor networks, and radio-frequency identification sensors, for quality analysis, especially of crops, fresh fruits, and vegetables. Mathiassen et al. (2011) reviewed the application of imaging technologies for inspecting fish and fish products and discussed the potential uses of visible/near-infrared light (VIS/NIR) imaging, VIS/NIR spectral imaging, computed tomography (CT), XRI, and MRI. Chen et al. (2013) reviewed advances in then-emerging imaging techniques and specifically focused on HSI, MRI, soft X-ray imaging, UI, TI, fluorescence imaging, and odor imaging for the quality assessment of agricultural products.

The present review covers imaging technologies in the context of an investigation of the internal properties of agricultural products, especially crops, fruits, vegetables, poultry, meat, fish, and seeds. These imaging technologies have significant potential with respect to the evaluation of internal properties. Hence, this review presents a discussion of HSI, MRI, soft X-ray, X-ray CT, TI, and UI. Future trends for imaging technologies are also discussed in the context of importance.

Imaging techniques

Hyperspectral imaging (HSI)

HSI is a powerful analytical tool for determining the characteristics of an object such as temperature (cold or hot), fat, and sugar content, and the presence of definite chemical elements. It has a diverse range of applications for the quality evaluation of agricultural products through the inspection of internal properties (Marshall, 2011). Mainstream cameras are limited to only capturing images with three spectral windows (red, green, and blue). However, hyperspectral cameras are used to capture an entire section of the electromagnetic spectrum at each pixel of an image. Each element has unique fingerprints in the electromagnetic spectrum, and these are termed spectrum signatures. Hyperspectral sensors and processing systems identify certain substances or chemical properties by their spectrum signatures. The hyperspectral images can be combined with three-dimensional (x, y, λ) hyperspectral data cubes (hypercube) to provide both spectral and spatial information simultaneously to describe a scene (Fig. 1).

Spectral imaging is classified into two categories, multispectral imaging (MSI) and HIS. The spectral resolution is the feature that distinguishes MSI from HSI (Barry et al., 2001). Images conventionally produced by the multispectral sensors contain between 3 and 10 different bands from the electromagnetic spectrum. Examples of bands include visible green, visible red, and near infrared. In contrast, hyperspectral sensors are more powerful with respect to the measurement of energy in narrower and more numerous bands corresponding to a maximum of 200 (or more) (GIS Geography, 2017; eXtension, 2017) (Fig. 2).

Additionally, HSI is classified into its two typical methods for image acquisition, namely staring image configuration and push-broom acquisition. When the image field of view is fixed, and the images are obtained one wavelength after another, the HSI has the staring image configuration. Conversely, the acquisition of simultaneous spectral measurements from a series of adjacent spatial positions is termed push-broom acquisition. More details can be found in Chen et al. (2013). The foundation and instrumentation of HSI were nicely reported by Ahmed et al. (2016). There are many benefits to using HSI, which includes short-wave infrared (SWIR), visible near-infrared (Vis-NIR), and Raman hyperspectroscopy, over other spectroscopy methods. Table 1 shows the features of HSI relative to RGB, NIR, and multispectral imaging (Gowen et al., 2007).

Several studies have focused on the application of HSI

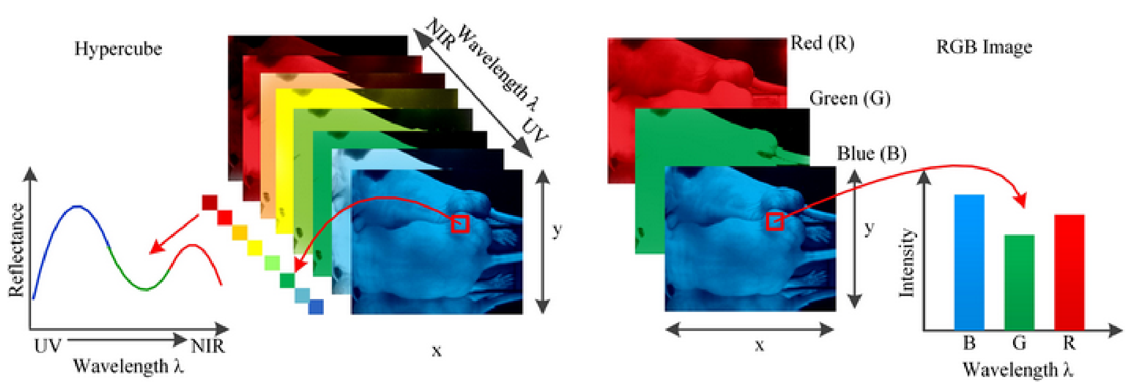

Figure 1. Comparison between hypercube and RGB image. A hypercube is a three-dimensional dataset of a two-dimensional image on each wavelength. The lower left represents the reflectance curve (spectral signature) of a pixel in the image. The RGB color image only possesses three image bands on the red, green, and blue wavelengths. The lower right shows the intensity curve of a pixel in the RGB image (Lu and Fei, 2014).

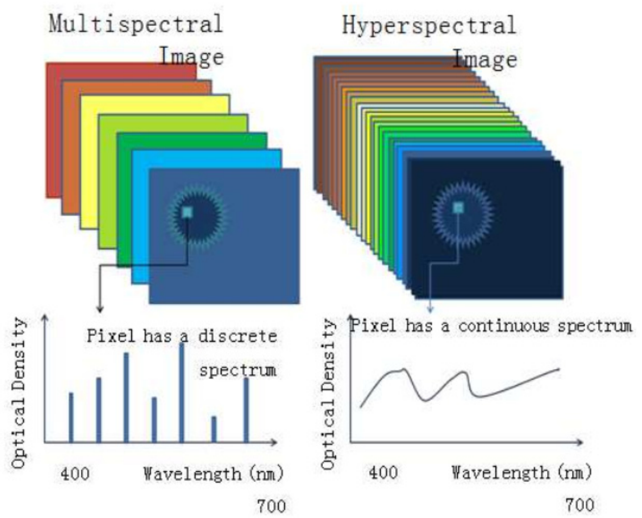

Figure 2. Comparison of multispectral imaging and HSI (Aboras et al. 2015).

Table 1. Comparison of RGB imaging, NIR spectroscopy (NIRS), multispectral imaging (MSI), and HSI

Feature	RGB imaging	NIRS	MSI	HSI
Spatial information	✓		✓	✓
Spectral information		✓	Limited	✓
Multi-constituent information	Limited	✓	Limited	✓
Sensitivity to minor component			Limited	✓

to investigate the internal properties of fruits for quality assessment. EIMasry et al. (2007) applied HSI in the visible and near-infrared (400-1000 nm) regions to measure the moisture content (MC), total soluble solids (TSS), and acidity (pH) of strawberries (Fig. 3). They obtained very high correlation coefficients (r) for predicting MC, TSS, and pH after applying a partial least squares (PLS) analysis to the spectral data. Several studies evaluated the internal properties of agricultural commodities by using HSI, and these included soluble solids content (SSC) and firmness measurement in Delicious and Gala apples with 93.5 % accuracy (Park et al., 2003); SSC and dry matter content (DMC) assessment in fruits, bulbs, and tubers (Peiris et al., 1999); firmness measurement of apples for quality evaluation (Peirs et al., 2002); starch, MC, and sugar content quantification in sweet potatoes with the minimum standard error of prediction (SEP) between 0.837 and 2 (Katayama et al., 1996); and acidity and pH computation in apples with 93 % prediction performance (Lammertyn et. al., 1998; Peirs et al., 2002).

A spectral range between 400 and 1000 nm was selected for using HSI to investigate physicochemical properties, such as pH, MC, TSS, and firmness of bananas and table grapes, by Rajkumar et al. (2012) and Baiano et al. (2012). The effect of temperature on the chemical properties of bananas was evaluated at three different temperatures (20°C, 25°C, and 30°C). Additionally, seven cultivars were examined in the investigation of the internal properties of table grapes. Both studies used a partial least squares regression (PLSR) to analyze the spectral data and observed good correlations between the chemical indices and the spectral data. Furthermore, the researchers explored the applications of HSI to other fruits including grapes, bell peppers, soybeans, blueberries, apples, mushrooms, and broccoli to evaluate their internal composition (Noh and Lu, 2007; Gowen et al., 2008; Gaston et al., 2010; Mendoza et al., 2011; Leiva-Valenzuela et al., 2013; Zhu et al., 2013; Huang et al., 2014; Schmilovitch et al., 2014; Nogales-Bueno et al., 2014; and Hernandez-Hierro et al., 2014). Rahman et al. (2017) measured the MC, pH, and SSC of tomatoes using HSI (Fig. 4). The study showed that, using a partial least squares (PLS) regression, the Savitzky-Golay (S-G) first-derivative preprocessed spectra resulted in more accurate values of MC and pH and the smoothing preprocessed spectra-based model resulted in a better estimation of SSC in intact tomatoes. Previously, Qin et al. (2011) evaluated lycopene in tomatoes using Raman chemical imaging. Munera et al. (2017) examined the internal quality of intact persimmons using VIS/NIR HSI. The main parameters involved the differences in the ripeness and level of astringency. At three selected optimal wavelengths (580, 680, and 1050 nm), 92% and 95% accuracy were obtained for ripeness and astringency, respectively.

In the meat industry, the determination of pH, color, moisture, and tenderness is an essential part of the quality inspection. Iqbal et al. (2013) studied turkey hams to predict moisture content, pH, and color by applying NIR HSI. The optimum wavelengths were selected for moisture content, pH, and color prediction using PLS regression analysis. The HSI technology also turned out to be an effective analytical tool for measuring the quality of fresh beef, lamb meat, and pork based on the chemical composition (Qiao et al., 2007; ElMasry et al., 2012; Kamruzzaman et al., 2012; Kamruzzaman et al., 2016).

Hyperspectral transmittance in the range of 750 nm to 1090 nm was used by Cogdill et al. (2004) to measure

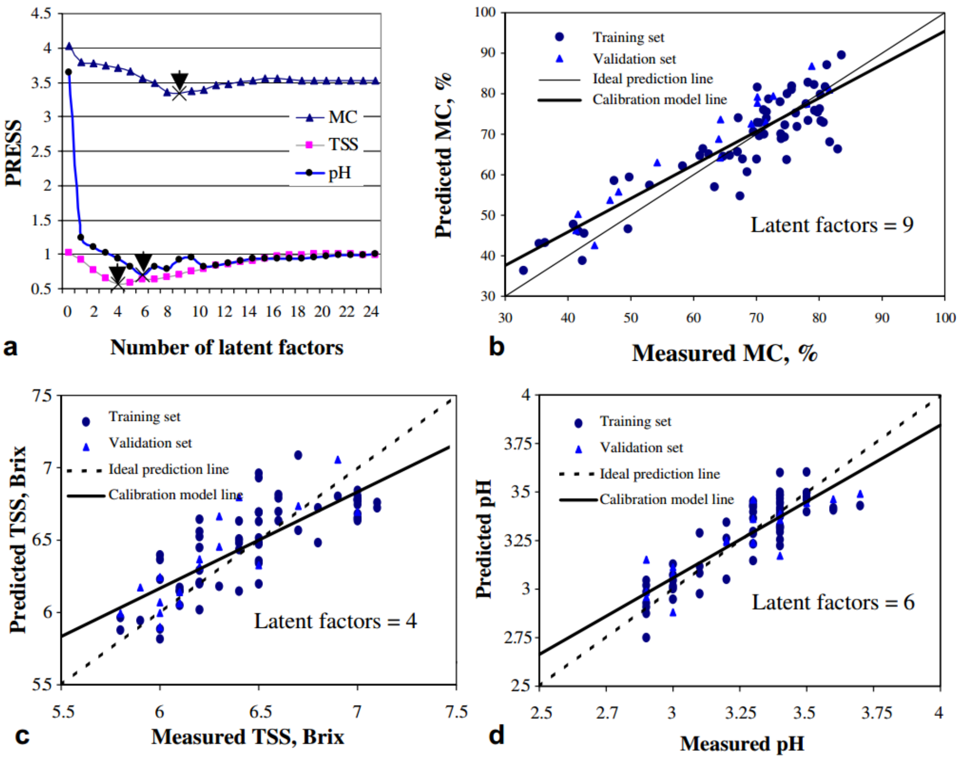

Figure 3. Prediction of MC, TSS, and pH using PLS models: (a) predicted residual error sum of squares (PRESS) to predict MC, TSS, and pH as a function of a number of factors, (b) measured and predicted MC values for training and validation sets using nine factors, (c) measured and predicted TSS values for training and validation sets using four factors, and (d) measured and predicted pH values for training and validation sets using six factors (ElMasry et al., 2007).

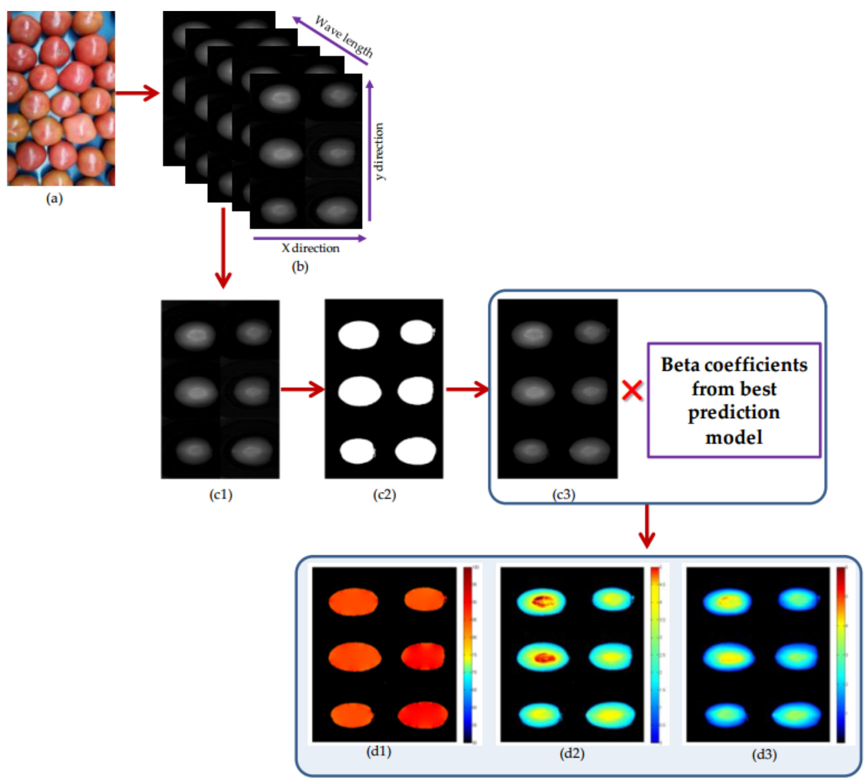

Figure 4. (a) Tomato samples; (b) 3-D hypercube of a tomato image; (c1) Corrected grayscale image at 1082 nm; (c2) Binary image at 0.1 threshold; (c3) Resultant grayscale image after masking with the previous image; (d1–d3) Chemical images of MC, pH, and SSC, respectively (Rahman et al., 2017).

moisture and oil content in maize for detecting the quality of maize kernels. Both partial least squares (PLS) regression and principal components regression (PCR) were used to develop the predictive calibration models, although they reported that a subsequent analysis of the oil calibration required improvements in the methods. Rodriguez-Pulido et al. (2013) studied the characterization of grapeseed based on chemical attributes with respect to their variety and maturity stage using NIR HSI. Senthilkumar et al. (2017) determined the significant wavelengths (1280 nm, 1300 nm, 1350 nm, and 1480 nm) for detecting ochratoxin in wheat seed with 100 % accuracy. However, the cost of HSI equipment is still high, and, thus, future development is essential to reducing the cost. Another prominent factor is improving the processing speed of the analysis to enhance the adoption of this emerging technique for the quality control of agricultural products.

Magnetic resonance imaging (MRI)

The spin magnetic moments of nuclei (particularly hydrogen) and resonant excitation are used in MRI to generate images of the interior of the material. The basic elements of an MRI system include: a magnet, with power-supply equipment, that produces a wide range of uniform, stable, and constant magnetic fields; a magnetic field coil with a controller and power-driven equipment; a radio-frequency (RF) producer; a computer system with substantial processing power and a large storage capacity for data collection; and additional apparatus (Chen et al., 2013). Nuclei containing an odd number of protons and/or neutrons exhibit a characteristic motion that is termed precession. A small magnetic moment is created by precession because nuclei are charged particles. Generally, agricultural products contain water, and hydrogen is a basic component of the water atom. Thus, the placement of a product in a large magnetic field causes several free hydrogen nuclei to align themselves in the direction of the magnetic field. The nuclei precession with respect to the magnetic field direction is termed Larmor precession, and its frequency (Larmor frequency) is proportional to the applied magnetic field strength. Subsequently, when a radio-frequency (RF) that is equal to the Larmor frequency is applied, the net magnetic moment is tilted away from the magnetic field. When the RF pulse is removed, the nuclei return to equilibrium, and, therefore, the net magnetic moment is parallel to the magnetic field again. This return to equilibrium is termed relaxation. At the time of relaxation, the nuclei lose energy and emit their own RF signals that are referred to as the free-induction decay (FID). This FID response signal is measured by a conductive field coil that is placed around the material. This measurement is processed by using a computer, and the MR images are finally reconstructed. NMR principles with a solid background and characteristics were adequately documented by previous studies (Belton et al., 2005; Farhat et al., 2007; Gudjonsdottir et al., 2009; Renou et al., 2011; Novoa-Carballal et al., 2011).

Proton density and relaxation time differ for each agricultural commodity and constitute the main parameters of the MRI technique. The information on these two parameters is used to identify the chemical composition and quantify the makeup of the product (Mariette, 2004). Suchanek et al. (2017) used a low-field MRI technique to determine the internal quality of Conference pears that were stored for six months under a controlled atmosphere. A change in the chemical composition of the fruits causes browning and internal voids that affect the dynamics of the tissue water and modifies the relaxation times of the proton in water. Thus, the relaxation time difference of the fruits was measured using the MRI technique to evaluate the water content, and that parameter effectively distinguished between damaged and healthy tissues inside the fruits, including browning and internal voids. The internal bruise damage measurement of fruits using MRI was reviewed by Opara and Pathare (2014). Several researchers applied MRI technology to investigate internal damage in agricultural products such as potatoes (Thybo et al., 2004), apples (McCarthy et al., 1995; Gonzalez et al., 2001; Marigheto et al., 2008; Melado-Herreros et al., 2013; Zhu et al., 2013; Defraeye et al., 2013; Melado-Herreros et al., 2015), tomatoes (Milczarek et al., 2009, Musse et al., 2009), watermelons (Saito et al., 1996), cucumbers (Kotwaliwale et al., 2012; Geng et al., 2015), mangos (Joyce et al., 2002), kiwi fruits (Taglienti et al., 2009), strawberries (Otero and Prestamo, 2009), and avocados (Chen et al., 1993).

The use of MRI permits the determination of the chemical composition, muscle structure, carcass composition, adipose tissue distribution, connective tissue, and muscle fiber type of meats. Meat properties, such as pH, water-holding capacity, moisture, texture, and sensory attributes, are directly related to the previously-listed parameters (Mitchell et al., 2001; Renou et al., 2003;

Ruiz-Cabrera et al., 2004; Shaarani et al., 2006; Herrero et al., 2007; Graham et al., 2010; Jung et al., 2010). Lee et al. (2015) used MRI combined with image processing to visualize and predict the intramuscular fat in beef. The results indicated a strong correlation between the MRI detected and chemically measured values. Collewet et al. (2004) demonstrated that a strong longitudinal relaxation time (T1) weighting of 1H images discriminated between the muscle and fatty tissue during visualization. Perez-Palacious et al. (2017) applied MRI techniques to predict the physicochemical characteristics of Iberian loin in a study in which they evaluated different acquisition sequences, computational texture feature algorithms, and data mining. The potential for using MRI to investigate meat and fish quality based on internal properties was summarized by Patel et al. (2015) and Xiong et al. (2017).

A study was conducted by Foucat et al. (1993) to investigate the morphology of germinating seeds by comparing the results of using of NMR and X-radiography techniques. The NMR images were recorded at a 1H frequency of 400 MHz with an in-plane resolution of 33 μm × 33 μm, and the result revealed the effectiveness of NMR. Pouliquen et al. (1997) successfully measured water and oil quantities in pea, maize, and wheat seeds and water content in lettuce, tomato, and radish seeds using NMR. Horigane et al. (2013) applied MRI to observe the moisture distribution in and discover the physicochemical properties of rice seeds. A few studies performed other experiments on the water soaking of rice seeds and beans and included those by Horigane et al. (2006) and Kikuchi et al. (2006).

X-ray imaging and CT

Wilhelm Conrad Roentgen discovered X-rays in 1895, and they are also eponymously known as Roentgen rays. They possess a wavelength range of 0.01-10 nm in the electromagnetic spectrum corresponding to frequencies in the range of 30-30,000 PHz with energies in the range of 120 eV-120 keV. Wavelengths in the range of 0.1-10 nm with photon energy in the range of 0.12-12 keV are termed soft X-rays, and those with wavelengths in the range of 0.01-0.1 nm containing energy in the range of 10-120 keV are termed hard X-rays. Hard X-rays possess high penetration ability with high radiation activity that can damage and contaminate agricultural products during the inspection. Hence, soft x-rays are more suitable for evaluating the internal density changes of agricultural products (Neethirajan et al., 2007). CT generates two-dimensional and three-dimensional images by accumulating X-ray images in the form of thin projected slices of a sample (Okochi et al., 2007).

According to Kotwaliwale et al. (2011), the basic components of X-ray imaging include the following: an X-ray source of electrons that produce X-ray photons with proper intensities; an X-ray converter (such as phosphor screen) that stops the X-ray from reaching the imaging medium with the aim of producing a visible output that is proportional to the incident X-ray photons; an imaging medium that captures the image; and a casing to protect the imaging medium from surrounding visible radiation. In comparison, a CT scanner incorporates an X-ray tube, collimators, turntable, and multichannel detectors that are installed in a confined hard chamber (Barcelon et al., 1999). In the CT scanner system, a collimated X-ray beam is directed to focus on a sample, and the detector measures the attenuated remnant radiation, and the response is transferred to a computer for processing and reconstructing the CT image. While scanning an object, the X-ray generator and multi-channel detectors rotate 360° around the object, and the detectors measure the quantity of X-ray energy transmitted through the scanned cross section of the object.

X-rays possess certain unique and significant characteristics including high penetration power, lack of deflection by magnetic fields, blackening of photographic film, producing photoelectric emission from and ionization of the gas, and glowing in exposed fluorescent objects to provide power for quality monitoring and other various methods of utilization. In medical diagnostics, X-ray imaging and CT are leading methods worldwide. X-ray imaging is also predominant in other areas such as security applications, luggage checking in airports, and inspecting mechanical or industrial elements. Recently, X-ray based (X-ray imaging and CT) quality monitoring systems were effectively applied as potential research tools to investigate the internal properties of agricultural commodities such as water core damage in apples (Kim and Schatzki, 2000), pinhole damage in almonds (Kim and Schatzki, 2001), internal defects of sweet onions (Tollner et al., 1999), and spit pits in peaches (Han et al., 1992).

A Talbot-Lau interferometer was used to apply a grafting based X-ray imaging to investigate the internal structure of fresh cherry tomatoes and dried umeboshi

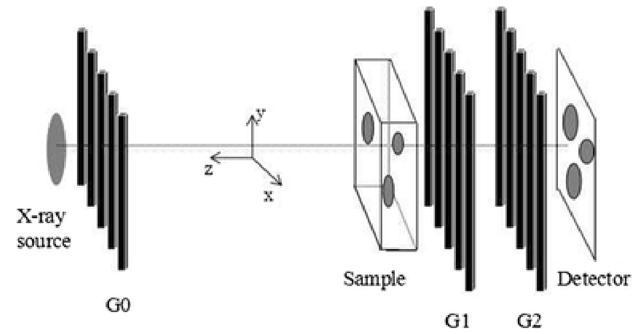

Figure 5. Schematic of an X-ray grating interferometer (Talbot-Lau interferometer). A microfocus X-ray generator is used with source grating (G0). G1 is the phase grating, and G2 is the amplitude grating (Wang et al., 2017).

by Wang et al. (2017). An X-ray grafting interferometer is shown in Figure 5. Conventional X-ray imaging only obtains the absorption information that is related to sample thickness and density. However, the use of grafting-based X-ray imaging allows the retrieval of absorption, refraction, and scattering images from the same set of the projected data, which is more robust for revealing abundant information with respect to the surface as well as the internal structure of the product.

Diels et al. (2017) used an X-ray CT technique to measure the bruise volumes in Jonagold, Jolly Red, and Kanzi apples. They measured the bruise volume using simple geometric assumptions for the destruction method and compared it with the results obtained from the CT image analysis. In the study, they also explored internal features such as cracks, water content, tissue density, and tissue damage. Donis-Gonzalez et al. (2012) also applied CT to investigate the internal properties, including air, decayed tissue, healthy tissue, and void space, of fresh chestnuts. The uses of X-ray CT for internal characterization of agricultural products were summarized by Donis-Gonzalez et al. (2014). X-ray and CT imaging techniques have also been involved in the internal quality monitoring of various items such as apples (Mitsuhashi-Gonzalez et al., 2010; Herremans et al., 2013; Herremans et al., 2014), pears (Lammertyn et al., 2003), pomegranates (Magwaza and Opara, 2014), sweet onions (Shahin et al., 2002), chicken (Tao et al., 2001), and fish (Mery et al., 2011). The potential uses of X-ray and X-ray CT for the internal quality evaluation of agricultural products were documented by Kotwaliwale et al. (2014). Overall, X-rays and CTs can be very effective for investigating the internal structural condition of agricultural products (Morita et al., 2003).

Jorge and Ray (2005) applied X-ray imaging analysis to investigate morphological distinctions between filled, partially filled, and unfilled guayule seeds to examine the relationship between internal structure and seed viability. The results indicated that the filled seeds exhibited higher germination viability as compared with partially filled and unfilled seeds. Additionally, X-ray tests were also used by Gomes et al. (2016) to evaluate the morphology of *Platypodium elegans Vog.* seeds to assess the relationship with germination. Seeds were classified based on their internal morphology as observed in the X-ray images, and germination tests were then performed to confirm the results of the radiographic image evaluation. Furthermore, X-rays and CTs were used to investigate the internal properties of several other types of seeds, including tomato seeds (Burg et al., 1994; Zhao et al., 2016), *Physalis peruviana* seeds (Fernandes et al., 2016), wild species seeds from Saudi Arabia (Al-Turki and Baskin, 2017), and bean seeds (Sood et al., 2016). Therefore, X-ray imaging is recommended as a technique to investigate seed quality by evaluating the internal properties of the seeds.

Thermal Imaging (TI)

All materials emit infrared (IR) rays when their material body temperatures exceed -273.15°C (0 K). If the temperature of the material is high, then the intensity of the emitted radiation is also high, and vice versa. Specifically, IR is part of the electromagnetic spectrum and is divided into four different regions: near infrared (0.75-3 μm), mid-infrared (3-6 μm), far infrared (6-15 μm), and extreme infrared (15-1,000 μm) (Meola and Carlomagno 2004). Thermal imaging (TI) involves measuring the intensity of radiation emitted from a material and converting the radiation pattern into a visible image. This is termed thermography or thermal imaging (Arora et al., 2008).

Generally, a TI system is equipped with a thermal camera, an optical system (containing a focusing lens, collimating lenses, and filters), a detector array, a signal processing unit, and an image processing unit, as shown in Figure 6 (Gowen et al., 2010). Normally, an illumination source is not required for TI technology. TI is classified into passive thermography and active thermography, based on the illumination requirement. In active thermography measurement, the integrated systems contain a

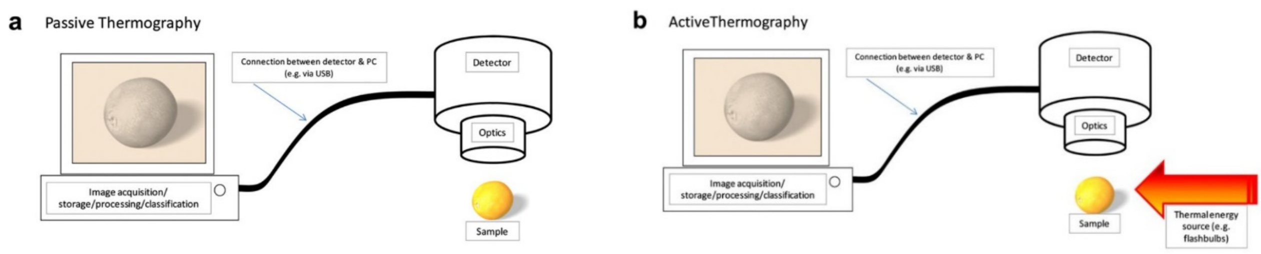

Figure 6. Components of a TI system in which "optics" represents the optical configuration of the system (e.g., the focusing lens, collimating lenses, and filters) and "detector" represents the planar array of sensors (e.g., microbolometers) (Gowen et al., 2010).

heating or cooling unit to obtain the thermal difference.

Additionally, TI devices are also categorized into cooled and uncooled devices. In an uncooled imaging device, the sensor elements are contained in a unit that operates at normal room temperature. In contrast, the cooled device sensor elements are contained in a unit in which the temperature is maintained below 0°C. The resolution and image quality is very high in a cooled TI device as compared with uncooled devices; however, the cooled devices are more expensive (Vadivambal and Jayas, 2011).

The potential use of active thermography for the determination of bruises in apples was assessed by Baranowski et al. (2009). A specific bruising procedure was applied to three varieties of apple (Jonagold, Champion, and Gloster). The apples were then kept at room temperature for 1 h. During the experiment, two halogen lamps were used to heat the samples, and a VIGOcam v50 thermal camera was used for image capture. The results demonstrated that the system could identify bruised apples at early stages and at various depths from the skin. Manickavasagan et al. (2008) developed a TI system to detect infestation in six of the development stages of *Cryptolestes ferrugineus* under the seed coat on the germ of a wheat kernel. They concluded that TI could potentially identify the infestation, although it was not as effective at detecting its development stage. Chelladurai et al. (2010) conducted another successful study of fungal infection in stored wheat using TI in which the images were obtained by an uncooled focal planar array thermal infrared camera.

To date, various studies have suggested that TI is a useful technique for investigating the internal conditions of agricultural products, including the maturity determination of apples and cherry tomatoes (Danno et al., 1977; Offerman et al., 1998; Hellebrand et al., 2000), wheat class identification (Manickavasagan et al., 2008a; 2008b), and tomato bruise detection (Vereycken et al., 2003). Costa et al. (2007) used thermography to assess the appropriateness of pork and ham samples for making dry-cured meat. The main objective of the experiment corresponded to an estimation of fat content, and they concluded that thermography is a fast and noninvasive technique to measure fat content. Weschenfelder et al. (2013) applied TI to investigate meat quality in the longissimus dorsi (LD), semimembranosus (SM), and adductor muscles of pigs and obtained satisfactory results.

Ultrasound imaging (UI)

The internal chemical composition of agricultural products plays an important role in determining the product quality. UI is a powerful analytical technique for evaluating the internal properties, such as chemical composition, structure, flow rate, physical state, and molecular properties, of agricultural commodities (McClements, 1997). Ultrasound is defined as mechanical waves at a frequency exceeding 20 kHz, which is above the upper limit of human hearing ability. The basic technique involves a high-frequency sound wave that is broadcast through the object to be tested, and information related to the properties of the object is then obtained by measuring the type and degree of interaction between the sound waves and object. There are two types of ultrasound imaging, namely high-intensity UI (the power level is typically between 10 and 1000 W/cm^2) and low-intensity UI (the power level is typically less than 1 W/cm^2). Low-intensity UI is preferred for the evaluation of agricultural product quality because the lower intensities do not result in any permanent modification of the physical or chemical properties of the products after removing the ultrasonic waves (Suslick, 1988). In contrast, high-intensity UI causes permanent chemical or physical changes in materials, and this is not acceptable for quality monitoring (Roberts, 1993).

The common key components of a UI system are as follows: (a) transducer, (b) signal generator, (c) digitizer, (d) display, and (f) measurement cell. The transducer design was described by Bashford et al. (1997) and Hutchins et al. (1998). The transducer converts electrical energy into mechanical energy, and the electrical input to the transducer is produced by a signal generator. When the signal returns from the transducer, it is converted into an analog electrical signal. Additionally, the digitizer converts the analog signal into a digital signal. Subsequently, a computer is used to display the signal, and image processing is performed to meet the requirements (McClements, 1997).

Agricultural products involve a complex mixture of various chemical and mineral compounds that should be monitored to maintain appropriate quality. Over the last few decades, several researchers assessed the applicability of UI for investigating the internal compounds of various products and found some potential for the UI technique. Xia et al. (2006) studied the impact of ultrasonic-assisted extraction for assessing the chemical and sensory quality of tea. Cho and Irudayaraj (2003) used UI to identify internal disorder for foreign object detection in cheese and chicken breasts. During ultrasound image acquisition, parameters including the velocity, relative attenuation, and attenuation coefficient of the samples were measured, and the scan area was set at 20 × 20 mm with spatial intervals of 1 mm. After processing the images, the result demonstrated that the UI performed well with respect to the detection of internal defects and foreign materials. Gan et al. (2006) reviewed the use of UI to identify physiochemical changes and density variations in food products for quality measurement purposes.

The estimation of the intramuscular fat content, muscle accretion, and body composition of beef cattle carcasses is very important for quality evaluation. The application of UI for this purpose was studied by Faulkner et al. (1990), Williams (2002), Ribeiro et al. (2008), and Chengcheng et al., (2009). Numerous researchers have applied real-time ultrasound to lamb and sheep carcasses to evaluate their chemical composition and degree of muscle development (Silva et al., 2005; Silva et al., 2006; Ribeiro et al., 2008; Theriault et al., 2009). This emerging technology has also been applied to study the internal composition of fish and poultry. The relationship between the ultrasonic properties and the fish moisture and protein content was investigated by Ghaedian et al. (1997) and Ghaedian et al. (1998). UI was assessed to be a rapid, nondestructive, noninvasive, and well-suited technique, as reviewed by Mohammadi et al. (2017), for dairy product quality assessments, such as microbial contamination detection, foreign body detection, and textural and compositional characterization.

Restraints and future trends

This review shows that imaging technology plays an important role in the internal quality monitoring of agricultural products. Knowledge related to imaging techniques is rapidly spreading, and agricultural industries are attracted to these internal quality measurement techniques. Most of the imaging techniques have very specific applications and are unable to simultaneously reveal all the internal aspects such as sugar content, dry matter content, acidity, and chemical composition. Therefore, further studies are required to determine how best to integrate a few techniques to measure all desired parameters simultaneously, and how to overcome the challenge of cost-effectiveness. The processing speed of the images is another main issue in online applications. Although modern cameras currently possess high-speed image acquisition capability in conjunction with high computer processing power, this equipment is still extremely expensive, so it is important to develop high-performance and low-cost equipment in the future.

Conclusions

Both internal and external parameters are important for the quality evaluation of agricultural products. This review presented a summary of imaging technologies that are well suited for revealing the internal properties of agricultural commodities. The potential and practical usages of HSI, MRI, X-ray and CT images, TI, and UI were discussed in the context of discovering the internal properties of agricultural products. Further studies will focus on the technical challenges of these imaging technologies.

Conflict of Interest

The authors have no conflicting financial or other interests.

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