Seed Science Research (2016) **26**, 285–305
doi:10.1017/S0960258516000234

REVIEW

Assessment of seed quality using non-destructive measurement techniques: a review

Anisur Rahman and Byoung-Kwan Cho*

Department of Biosystems Machinery Engineering, College of Agricultural and Life Science, Chungnam National University, 99 Daehak-ro, Yuseong-gu, Daejeon 305-764, Republic of Korea

Abstract

Seed quality is of great importance in optimizing the cost of crop establishment. Rapid and non-destructive seed quality detection methods must therefore be developed for agriculture and the seed production industry. This review focuses primarily on non-destructive techniques, namely machine vision, spectroscopy, hyperspectral imaging, soft X-ray imaging, thermal imaging and electronic nose techniques, for assessing the quality of agricultural seeds. The fundamentals of these techniques are introduced. Seed quality, including chemical composition, variety identification and classification, insect damage and disease assessment as well as seed viability and germinability of various seeds are discussed. We conclude that non-destructive techniques are accurate detection methods with great potential for seed quality assessment.

Keywords: non-destructive measurement, seed classification, seed damage, seed quality, seed viability

Nomenclature

ADF	acid detergent fiber
ANNR	artificial neural network regression
ANN	artificial neural network
BPNN	back-propagation neural network
DA	discriminant analysis
DM	dry matter
ECVA	extended canonical variates analysis
FDA	factorial discriminant analysis
ICA	independent component analysis
iECVA	interval extended canonical variates analysis
iPLS-DA	interval partial least-squares discriminant analysis
iPLSR	interval partial least-squares regression
KNN	k-nearest neighbor
KPCA	kernel principal component analysis
KS	Kennard and Stone
LDA	linear discriminant analysis
LOD	limit of detection
LSD	least significance difference
LS-SVM	least-squares support vector machine
LS-SVMR	least-squares support vector machine regression
LW-PCA	locally weighted principal component analysis
MD	Mahalanobis distance
MDC	Mahalanobis distance classifier
MLMR	maximum likelihood multinomial regression
MLP	multilayer perceptron
MLR	multiple linear regression
MPLS	modified partial least-squares
MPLSR	modified partial least-squares regression
MSE	mean squared error
NDA	non-linear discriminant analysis
NNN	non-linear neural networks
OMD	organic matter digestibility
PCA	principal component analysis
PCR	principal component regression
PLS	partial least-squares
PLS-DA	partial least-squares discriminant analysis
PLSR	partial least-squares regression
QDA	quadratic discriminant analysis
RF	random forest
SAM	spectral angle mapper
SIMCA	soft independent modeling class analogy
SSC	soluble sugar content
SWI	single waveband image
SVDD	support vector machine description
RMSEP	root mean square error of prediction
R_p	correlation coefficient of prediction
R	coefficient of correlation
R^2	coefficient of determination
R_p^2	determination coefficient of prediction
R_c^2	determination coefficient of calibration
SEP	standard error of prediction
RPD	ratio prediction to deviation

* Correspondence
Email: chobk@cnu.ac.kr

Introduction

Seed is a living product and must be grown, harvested and processed correctly to maximize its viability and subsequent crop productivity. Seed quality has a profound effect on the development and yield of a crop

(Bradbeer, 1988). Good seed quality can increase yield significantly. Seed quality depends on the health, physiology, germinability and physical attributes of seeds, including the presence or absence of disease, chemical composition, insect infestation, and the presence or absence of weed seeds or other plant varieties. Quality of seeds and their products is directly or indirectly related to human health; nevertheless, the evaluation of seed quality parameters is a time-consuming process. For example, calculation of the germination percentage commonly requires manual counting and grading of germinating seedlings by experienced technicians. Therefore rapid, simple and accurate detection techniques must be developed for farmers and the agro-industry to ensure quality seed during seeding, growth, harvesting, storage and transport to consumers (Huang *et al.*, 2015).

The sowing quality of seed is associated with the germination and growth conditions after sowing and depends on seed composition, kernel maturity, insect infestation, diseases, cleanliness and germination ability (Copeland and McDonald, 1999). The genetic purity of seeds may be detected by molecular identification, DNA analysis, isotope fingerprinting and mineral element analysis (Bradbeer, 1988). Protein electrophoresis, gas chromatography, high-performance liquid chromatography, tetrazolium tests, accelerated ageing and conductivity tests have been employed to evaluate the vigour and germination quality of seeds (Huang *et al.*, 2015). Most of these chemical and physical techniques exhibit high accuracy and good reliability but have certain limitations, such as their high cost, long time requirements and high operator requirements. With the increasing demand for rapid, non-destructive and reliable techniques for evaluation of seed quality in the modern agro-industry, high-performance techniques must be developed for the evaluation of seed quality. A number of non-destructive testing technologies have been developed for evaluation of seed quality (Huang *et al.*, 2015). These non-destructive testing technologies are rapid, accurate, reliable and simple methods for assessing the quality of seeds. This review focuses primarily on non-destructive techniques, namely, machine vision, spectroscopy, hyperspectral imaging, electronic nose, soft X-ray imaging and thermal imaging techniques, which have been used to assess seed quality parameters such as chemical composition, genetic purity and classification, disease and insect infestation, as well as vigour and germinability. The emphasis in this review is also placed on insights into the methods and techniques that have been investigated for evaluating seed qualities.

Non-destructive techniques for seed quality assessment

Machine vision

Machine vision, also known as 'computer vision' or 'computer image processing', is an artificial intelligence technique that simulates human vision (Huang *et al.*, 2015). This technique is non-destructive, reliable and rapid and has been proven to be an effective and powerful technique for quality evaluation of food and agricultural products, particularly seeds (Hornberg, 2007). A typical machine vision system consists of four basic components: an illumination system, a sensor or camera, a lens and a computer with frame grabber/digitizer (Fig. 1). Most applications of machine vision address the visible spectrum (380–780 nm) (Gunasekaran *et al.*, 1985). A machine vision system should be capable of identifying and grading seeds based on image external features, such as size, shape, colour and texture. The superiority, disadvantages and feasibility of different image external features should be simultaneously considered to select the most suitable feature for specific applications. Machine vision has already been used, with varying success, to assess seeds of a range of crop and non-crop species. This review focuses mainly on machine vision techniques that can be used to classify seed varieties, disease detection, identification of seed varieties, etc.

Spectroscopy

Spectroscopy is used to investigate and measure the spectra produced when matter interacts with, or emits, electromagnetic radiation (Huang *et al.*, 2015). A range of spectroscopic techniques, such as near-infrared- (NIR), mid-infrared- (MIR), fluorescence-, Fourier transform-infrared- (FT-IR) and Raman spectroscopy have been

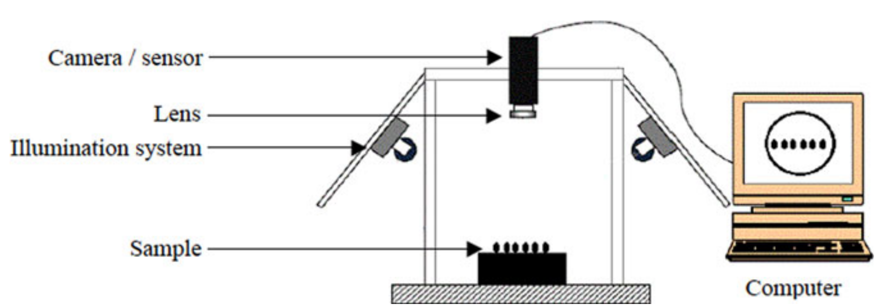

Figure 1. A typical machine vision system

https://doi.org/10.1017/S0960258516000234 Published online by Cambridge University Press

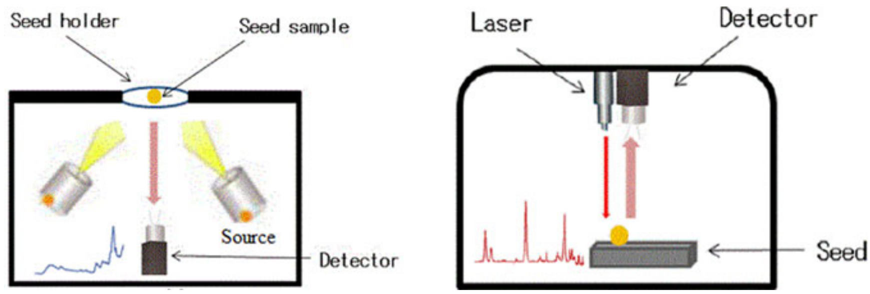

Figure 2. NIR, MIR or FT-IR spectroscopy (left panel) and Raman spectroscopy (right panel). From Seo *et al.* (2016).

widely and successfully used as sensitive and fast analytical techniques for authentication and quality analysis of a variety of agricultural seeds (Fig. 2). NIR and MIR spectroscopy are based on molecular overtones and combined vibrations. FT-IR spectroscopy is a technique used to record infrared spectra and detect radiation in the MIR region. FT-IR spectroscopy is an information-rich analytical technique, as it provides a greater amount of chemical information regarding the scanned sample than NIR spectroscopy (Lohumi *et al.*, 2015). Raman spectroscopy is another form of analytical spectroscopy that is suitable for quality and authenticity analysis of agro-food products. This technique can provide specific information needed for identification of sample matrices based on model compounds, such as lipids, proteins and carbohydrates, and is sensitive to minor components (Seo *et al.*, 2016). This review focuses mainly on spectroscopic techniques that can be used to detect seed quality attributes, such as chemical composition, viability and damage by insects and other causes.

Hyperspectral imaging

Hyperspectral imaging has recently emerged as a powerful analytical technique for food quality and authenticity analysis. This technique is used to acquire both spectral and spatial information from an object (Wu and Sun, 2013). A hyperspectral imaging system includes light sources, wavelength dispersion devices and detectors. As the centre of a hyperspectral imaging system, wavelength dispersion devices are used to disperse broadband light into different wavelengths (Fig. 3). The detector collects light, which carries useful information from the wavelength dispersion device and measures the intensity of the light by converting radiation energy into electrical signals (Huang *et al.*, 2015). Using hyperspectral imaging, sample analysis is convenient and comparatively fast because a large number of samples are analysed at the same time, whereas spectroscopic methods analyse only one sample at a time (Lohumi *et al.*, 2015). Machine vision and spectroscopy can only provide spatial or spectral information, whereas hyperspectral imaging, which integrates machine vision and spectroscopy advantages, can simultaneously obtain spatial and spectral information by using only one system. In this regard, hyperspectral imaging has been widely used by researchers to evaluate the exterior quality of seeds and predict their internal composition (Mahesh *et al.*, 2011a; Zhu *et al.*, 2011; Huang *et al.*, 2014).

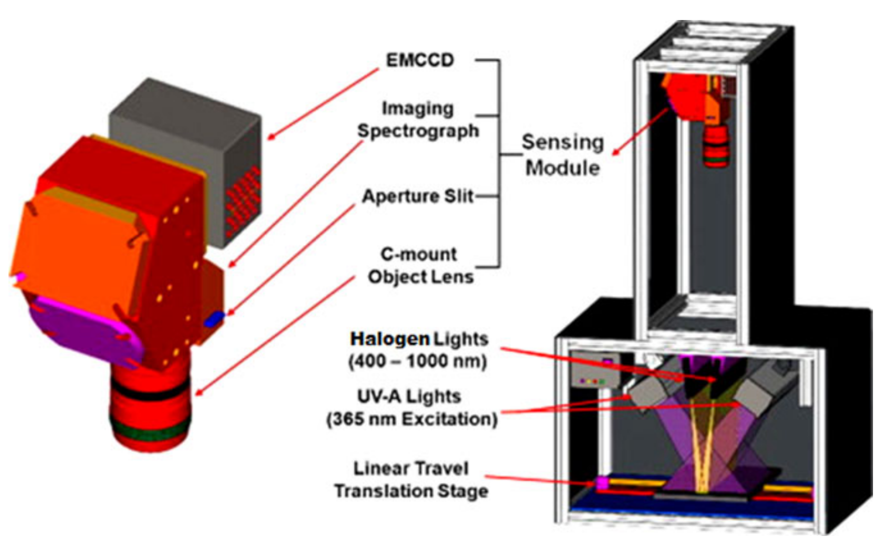

Figure 3. A typical hyperspectral reflectance/fluorescence imaging system. From Qin *et al.* (2013).

https://doi.org/10.1017/S0960258516000234 Published online by Cambridge University Press

Thermal imaging

Thermal imaging is a technique for converting the invisible radiation pattern of an object into visible images for feature extraction and analysis without establishing contact with the object. Using this method, the surface temperature of any object can be mapped at a high resolution in two dimensions. The thermal data produced may be used directly or indirectly in many ways (Manickavasagan *et al*., 2008). The application of thermal imaging has gained popularity in the agro-food industry in recent years (Vadivambal and Jayas, 2011). The major advantage of thermal imaging is that it is a non-contact, non-invasive and rapid technique that can be used in online applications (Fig. 4). Thermal cameras are easy to handle and highly accurate temperature measurements are possible (Vadivambal and Jayas, 2011). Using thermal imaging, it is possible to obtain temperature mapping of any particular region of interest with fast response times, which is not possible with thermocouples or other temperature sensors that can only measure spot data. The repeatability of temperature measurements in thermal imaging is high (Ishimwe *et al*., 2014). In addition, thermal imaging does not require an illumination source, unlike other imaging systems. Nowadays, thermal imaging has a potential application in many operations involved in agriculture, starting from assessing seed quality, especially in detection of diseases, insects and seedling viability, estimating soil water status, estimating crop water stress, scheduling irrigation, determining disease and pathogen affected plants, estimating fruit yield and evaluating maturity of fruits and vegetables (Chelladurai *et al*., 2010; Manickavasagan *et al*., 2010; Vadivambal and Jayas, 2011). In spite of the fact that it could be used as a non-contact, non-destructive technique, it has some drawbacks in comparison with other imaging techniques because high resolution thermal imaging is costly and accurate thermal measurements depend on environmental and weather conditions. Thus it may not be possible to develop a universal methodology for its application in seed quality assessment.

Soft X-ray imaging

Electromagnetic waves with wavelengths ranging from 1 to 100 nm (and energies of approximately 0.12 to 12 keV) are called soft X-rays. The low penetration power of these waves and their ability to reveal internal density changes make soft X-rays suitable for use in evaluating agricultural products (Neethirajan *et al*., 2007). Soft X-ray imaging is a well-known technique that takes a few seconds (3–5 s) to produce an X-ray image. Soft X-ray imaging has begun to be used in the seed industry to detect internal voids, defects, insect infestation and insect damage (Karunakaran *et al*., 2004; Neethirajan *et al*., 2006; Mathanker *et al*., 2013).

Electronic nose

An electronic nose is an instrument consisting of an array of electronic and chemical sensors with partial specificity and a pattern recognition system that is capable of recognizing simple or complex odours (Wilson and Baietto, 2009). These devices typically have arrays

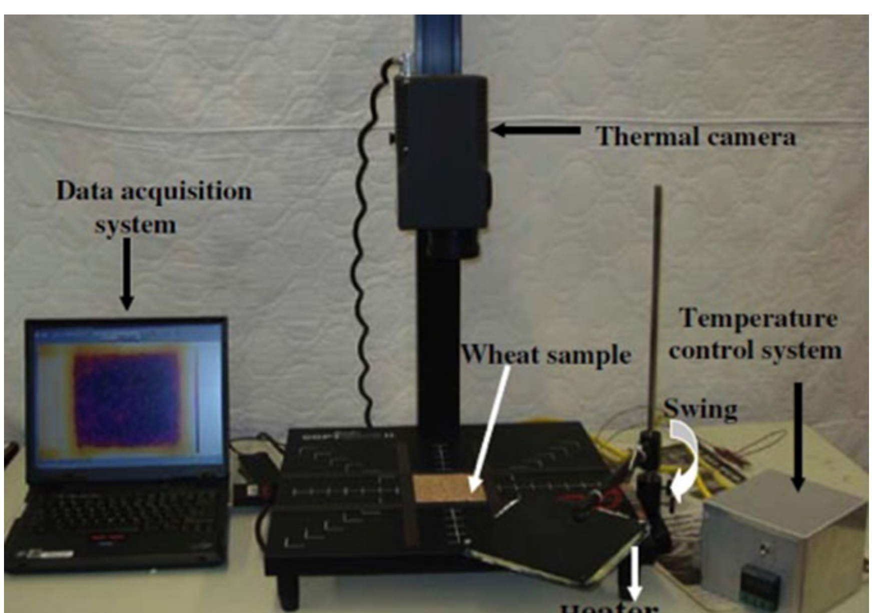

Figure 4. A typical thermal imaging system. From Manickavasagan *et al*. (2010).

of sensors used to detect and distinguish odours precisely in complex samples and at low cost (Zhou *et al.*, 2012). Electronic nose devices have been employed in a wide variety of applications, including classification of kernels and microbial pathogen detection.

Quality detection of seeds using non-destructive techniques

Quality assessment of seeds: chemical composition

In recent years, non-destructive sensing techniques, mainly spectroscopy and hyperspectral imaging, have been widely used to determine the internal composition of seeds (Table 1). Previous studies have shown that spectroscopy systems can be applied successfully to determine the protein contents of corn (Armstrong *et al.*, 2011), maize (Baye *et al.*, 2006), common beans (Hacisalihoglu *et al.*, 2010), rice (Wu and Shi 2004), soybean (Ferreira *et al.*, 2014), peanuts (Wang *et al.*, 2012), jatropha (Vaknin *et al.*, 2011), rapeseed (Velasco and Möllers, 2002), sunflower (Fassio and Cozzolino, 2004), canola (Daun *et al.*, 1994), cotton (Huang *et al.*, 2013), foxtail millet (Yang *et al.*, 2013), flax, safflower, sesame and palm (Pandord *et al.*, 1988). Previous studies have shown that spectroscopy is highly accurate in protein prediction. The coefficients of determination for prediction (R_{P}^2) of a partial least-squares regression (PLSR) model have been found to be 0.98 for corn (Chen *et al.*, 2014), 0.99 for rapeseed (Pandord *et al.*, 1988), 0.96 for cottonseed (Huang *et al.*, 2013), 0.98 for peanut (Pandord *et al.*, 1988) and 0.91 for soybeans (Ferreira *et al.*, 2014). Spectroscopy has also been used to estimate the fibre content of soybean, corn (Armstrong *et al.*, 2011) and rapeseed (Wittkop *et al.*, 2012; Bala and Singh, 2013;), and the sucrose content of soybean (Choung, 2010). However, unsatisfactory results have been reported for carbohydrate determination in maize (Baye and Becker 2004; Tallada *et al.*, 2009), rice (Wu and Shi 2004), foxtail millet (Chen *et al.*, 2013) and soybean (Choung 2010; Ferreira *et al.*, 2013) and made the same conclusions in their study that any changes in the compositional amount among the sample are not translated into differences within the spectra. In recent research, hyperspectral imaging has been used to predict crude protein and crude fat fractions in soybean (Zhu *et al.*, 2011), protein in wheat (Mahesh *et al.*, 2011a) and alpha-amylase activity in wheat (Xing *et al.*, 2009, 2011). Unsatisfactory prediction results have been obtained in some cases using hyperspectral imaging because of the difficulty of extracting the most important object features for assessing the physical structure and chemical composition of samples. The oil content is an important parameter in the internal quality evaluation of most oilseed crops. Spectroscopy within the range of 400–2500 nm has been widely used to determine oil content in peanuts (Sundaram *et al.*, 2010), maize (Tallada *et al.*, 2009), safflower (Rudolphi *et al.*, 2012), rapeseed (Velasco and Becker, 1998; Velasco *et al.*, 1999; Petisco *et al.*, 2010), sunflower (Pandord *et al.*, 1988; Pérez-Vich *et al.*, 1998; Fassio and Cozzolino, 2004), jatropha (Vaknin *et al.*, 2011), canola (Daun *et al.*, 1994), cotton (Huang *et al.*, 2013), corn and soybean (Armstrong *et al.*, 2011). The coefficients of determination of the oil prediction model were 0.99, 0.91, 0.98, 0.92, 0.95, 0.98, 0.95, 0.87 and 0.84 for peanut, safflower, rapeseed, sunflower, jatropha, canola, cotton, corn and soybean, respectively. Hyperspectral imaging has also been used to predict the oil and oleic acid concentrations in corn (Weinstock *et al.*, 2006). An NIR hyperspectral imaging system (750–1090 nm) was used to predict the oil content in maize and the determination coefficient of the PLSR model for the determination of oil content was found to be 0.75 (Cogdill *et al.*, 2004). The results indicated outstanding performance of the non-destructive technique in the prediction of the internal composition of the seed. Spectroscopy has also been used to determine the fatty acid content of peanuts (Sundaram *et al.*, 2010), soybean (Patil *et al.*, 2010), safflower (Rudolphi *et al.*, 2012), rapeseed (Kim *et al.*, 2007), sunflower (Cantarelli *et al.*, 2009), jatropha (Vaknin *et al.*, 2011), canola and flax (Siemens and Daun, 2005) with high accuracy. The amino acid composition of seeds is also a concern in their quality assessment since high protein content and a rational amino acid composition of seed are a major concern to the plant breeder (Chen *et al.*, 2011). Studies have shown that near-infrared spectroscopy (NIRS) and FT-NIRS can be used successfully in the assessment of amino acid composition in rapeseed (Pandord *et al.*, 1988; Chen *et al.*, 2011), peanuts (Wang *et al.*, 2012), rice (Zhang *et al.*, 2011) and foxtail millet (Yang *et al.*, 2013). An experiment in high-resolution hyperspectral reflectance imagery in the near-infrared region (960–1700 nm) was conducted to predict the amino acid content of fresh soybeans and showed that the best predictions (MSE = 0.305, $R = 0.611$) were obtained using a non-linear artificial neural network (ANN)-based regression model based on the second-derivative spectra data produced for the nitrogen concentration (Monteiro *et al.*, 2007). Spectroscopy has also been used to determine the moisture content of soybean (Pandord *et al.*, 1988; Ferreira *et al.*, 2013; Ferreira *et al.*, 2014), sunflower (Pandord *et al.*, 1988; Fassio and Cozzolino, 2004), peanuts (Sundaram *et al.*, 2010), flax, safflower and cotton (Pandord *et al.*, 1988), as well as the pH of cocoa beans (Sunoj *et al.*, 2016), the mineral contents (K, Mg, Ca and P) of peanuts (Phan-Thien *et al.*, 2011), the seed weight of rapeseed (Velasco *et al.*, 1999), the grain weight of rice and brown rice (Wu and Shi, 2004), the ethanol content of

Table 1. Assessment of chemical composition in seeds using different non-destructive techniques

Chemical composition	Seed	Method	Spectra region (nm)	Analysis method (s)	Result	References
Protein, starch	Bean	Spectroscopy	907–1689	PLSR	$R_p^2 = 0.80–0.88$	Hacisalihoglu *et al.*, 2010
Protein, starch, amylose	Bean	Spectroscopy	1000–2500	PCA, PLSR	RPD = 2.6–3.7	Plans *et al.*, 2013
Fatty acid	Canola seed	Spectroscopy	400–2500	MPLSR	SEP = 0.42–0.77%	Siemens and Daun, 2005
Oil, protein	Canola seed	Spectroscopy	850–1050	PLSR, MLR	SEP = 0.43–0.55%, 0.35–0.42%	Daun *et al.*, 1994
pH, polyphenol	Cocoa bean	FT-NIR spectroscopy	3600–12500 cm^{-1}	PLSR	$R_p^2 = 0.80, 0.85$	Sunoj *et al.*, 2016
Oil, oleic acid	Corn	Hyperspectral imaging	950–1700	PLSR	RMSEP = 0.74%, 14%	Weinsto1ck *et al.*, 2006
Protein, fat	Corn	Spectroscopy	1000–2500	PLSR	$R_p^2 = 0.98, 0.94$	Chen *et al*. 2014
Protein, oil, starch, density	Corn	Spectroscopy	904–1685	PLSR	$R_p^2 = 0.68–0.91$	Armstrong *et al.*, 2011
DM, protein, ADF, OMD	Corn	Spectroscopy	400–2500	PCA, PLSR	$R_p = 0.42–0.92$	Fassio *et al.*, 2009
Moisture, oil, protein, crude fibre	Cotton	Spectroscopy	1100–2500	MLR	$R = 0.98, 0.99, 0.98, 0.95$	Pandord *et al.*, 1988
Protein, oil	Cotton	Spectroscopy	1100–2498	PLSR, LS-SVMR	$R_p^2 = 0.96, 0.95$	Huang *et al*. 2013
Fatty acid	Flax seed	Spectroscopy	400–2500	MPLSR	SEP = 0.62–1.2%	Siemens and Daun, 2005
Moisture, oil, protein, crude fibre	Flax seed	Spectroscopy	1100–2500	MLR	$R = 0.96, 0.99, 0.99, 0.98$	Pandord *et al.*, 1988
Protein, carbohydrates, fat	Foxtail millet	Spectroscopy	950–1650	MLR	$R_p^2 = 0.70–0.94$	Chen *et al.*, 2013
Protein, fat, starch, amino acids	Foxtail millet	Spectroscopy	800–2500	PLSR	$R_p^2 = 0.71–0.93$	Yang *et al.*, 2013
Protein, oil content, composition	Jatropha	Spectroscopy	1100–2498	MPLSR	$R_p^2 = 0.86, 0.91–0.95, 0.10–0.73$	Vaknin *et al.*, 2011
Moisture, oil content	Maize	Hyperspectral imaging	750–1090	PLSR	$R_p^2 = 0.87, 0.75$	Cogdill *et al.*, 2004
Ethanol yield	Maize	Spectroscopy	400–2498	PLSR	RMSEP = 0.56%	Hao *et al.*, 2012
Protein	Maize	Spectroscopy	400–2500	MLR	$R_p^2 = 0.94$	Rosales *et al.*, 2011
Protein, oil, SSC	Maize	Spectroscopy	904–1685	PLSR	$R_p^2 = 0.25–0.89$	Tallada *et al.*, 2009
Protein, starch	Maize	Spectroscopy	890–1700	PLSR	SEP = 1.7%, 11.5%	Baye *et al.*, 2006
Mineral: Ca, K, Mg, P	Peanut	Spectroscopy	400–2498	PLSR	$R_p^2 = 0.172–0.792$	Phan-Thien *et al.*, 2011
Moisture, oil, protein, crude fibre	Peanut	Spectroscopy	1100–2500	MLR	$R = 0.98, 0.99, 0.99, 0.98$	Pandord *et al.*, 1988
Protein, amino acid	Peanut	Spectroscopy	950–1650	PLSR	$R_p^2 = 0.99, 0.83–0.96$	Wang *et al.*, 2012
Moisture content	Peanuts	Spectroscopy	400–2500	PLSR	$R_p^2 = 0.84–0.97$	Sundaram *et al.*, 2010
Oil, fatty acids	Peanuts	Spectroscopy	400–2500	PLSR	$R_p^2 = 0.99$	Sundaram *et al.*, 2010
Moisture, oil, protein, crude fibre	Palm	Spectroscopy	1100–2500	MLR	$R = 0.79, 0.78, 0.71, 0.57$	Pandord *et al.*, 1988
Amino acid	Rapeseed	Spectroscopy	1100–2498	MPLSR	$R_p^2 = 0.89–0.98$	Chen *et al.*, 2011
Fatty acid	Rapeseed	Spectroscopy	400–2500	MPLSR	$R_p^2 = 0.95–0.98$	Velasco and Becker, 1998
Fatty acid	Rapeseed	Spectroscopy	1100–2500	MPLSR	$R_p^2 = 0.72–0.98$	Kim *et al.*, 2007

Table 1. *Continued*

Chemical composition	Seed	Method	Spectra region (nm)	Analysis method (s)	Result	References
Fibre content	Rapeseed	Spectroscopy	400–2500	PCA, MPLSR	$R_p^2 = 0.53–0.81$	Wittkop *et al.*, 2012
Moisture, oil, protein, crude fibre	Rapeseed	Spectroscopy	1100–2500	MLR	$R = 0.99$, 1.0, 0.99, 0.99	Pandord *et al.*, 1988
Oil, protein	Rapeseed	Spectroscopy	400–2498	PCA, MPLSR	$R_p^2 = 0.98$, 0.96	Petisco *et al.*, 2010
Phenol, crude fibre	Rapeseed	FT-NIR spectroscopy	3600–12800 cm^{-1}	PLSR	$R_p^2 = 0.96$, 0.91	Bala and Singh, 2013
Protein	Rapeseed	Spectroscopy	1100–2500	MPLSR	$R = 0.94$	Velasco and Möllers, 2002
Seed weight, oil, fatty acid	Rapeseed	Spectroscopy	1100–1460 and 1560–2500	MPLSR	$R = 0.92$, 0.92, 0.73–0.94	Velasco *et al.*, 1999
Amino acid	Rice	Spectroscopy	1100–2498	PCR	$R_p^2 = 0.84–0.95$	Zhang *et al.*, 2011
Grain weight, brown rice weight, amylose content	Rice	Spectroscopy	1100–2500	MLR	$R_p^2 = 0.67$, 0.71, 0.85	Wu and Shi, 2004
Starch, protein	Rice	Spectroscopy	1100–2500	PLSR, LS-SVM, ICA	$R_p = 0.89–0.98$	Shao *et al.*, 2011
Amylose, protein	Rice	Spectroscopy	1100–2500	LS-SVM, ANN	$R_p = 0.82-0.88$	Shao *et al.*, 2009
Moisture, oil, protein, crude fibre	Safflower	Spectroscopy	1100–2500	MLR	$R = 0.85$, 0.97, 0.77, 0.84	Pandord *et al.*, 1988
Moisture, oil, protein, crude fibre	Sesame	Spectroscopy	1100–2500	MLR	$R = 0.99$, 0.99, 0.99, 0.75	Pandord *et al.*, 1988
Colour, moisture	Soybean	Hyperspectral imaging	400–1000	PLSR	$R_p = 0.83$, 0.97	Huang *et al.*, 2014
Fatty acid	Soybean	Spectroscopy	850–1048	PLSR, ANN, LS-SVM	SEP = 0.42–1.67%	Igne *et al.*, 2008
Fatty acid	Soybean	Spectroscopy	850–1048	PLSR	SEP = 0.01–0.08%	Hurburgh, 2007
Fatty acid	Soybean	Spectroscopy	850–1048	PLSR, ANN, SVMR	$R_p^2 = 0.67–0.94$	Kovalenko *et al.*, 2006
Fatty acid	Soybean	Spectroscopy	850–1048	MPLSR	$R_p^2 = 0.63–0.89$	Patil *et al.*, 2010
Moisture, oil, protein, crude fibre	Soybean	Spectroscopy	1100–2500	MLR	$R = 0.92$, 0.99, 0.99, 0.76	Pandord *et al.*, 1988
Moisture, protein, lipid	Soybean	Spectroscopy	1000–2500	PLSR	$R_p^2 = 0.50–0.81$	Ferreira *et al.*, 2013
Moisture, ash, protein, lipid	Soybean	Spectroscopy	1000–2500	PLSR	$R_p^2 = 0.63–0.91$	Ferreira *et al.*, 2014
Oil, linoleic, oleic acid	Soybean	Spectroscopy	400–2500	MPLSR	$R_p^2 = 0.91$, 0.73, 0.68	Rudolphi *et al.*, 2012
Protein, fat	Soybean	Hyperspectral imaging	850–1700	PLSR	$R_c^2 = 0.9$, 0.97	Zhu *et al.*, 2011
Protein, oil content	Soybean	Raman spectroscopy	200–1800 cm^{-1}	iPLSR	$R_p^2 = 0.92$, 0.87	Lee *et al.*, 2013
Protein, oil, fibre	Soybean	Spectroscopy	904–1685	PLSR	$R_p^2 = 0.44-0.90$	Armstrong *et al.*, 2011
Sucrose	soybean	Spectroscopy	400–2500	MPLSR	$R_p^2 = 0.92$	Choung, 2010
Sweetness, amino acid	Soybean	Hyperspectral imaging	400–1000	ANNR	$R = 0.61$, 0.60–0.74	Monteiro *et al.*, 2007

Continued

Table 1. *Continued*

Chemical composition	Seed	Method	Spectra region (nm)	Analysis method (s)	Result	References
Fatty acid	Sunflower	Spectroscopy	400–2500	MPLSR	$R_p^2 = 0.94$	Moschner and Biskupek-Korell, 2006
Moisture, crude protein, oil	Sunflower	Spectroscopy	400–2500	MPLSR	$R_p^2 = 0.0.95, 0.96, 0.9$	Fassio and Cozzolino, 2004
Moisture, oil, protein, crude fibre	Sunflower	Spectroscopy	1100–2500	MLR	$R = 0.96, 1.0, 0.99, 0.99$	Pandord *et al.*, 1988
Oil, fatty acid	Sunflower	Spectroscopy	1100–2500	MPLSR	$R_p^2 = 0.92, 0.97–0.99$	Pérez-Vich *et al.*, 1998
Oleic acid	Sunflower	Spectroscopy	1596–1794	PLSR	LOD = 3.4%	Cantarelli *et al.*, 2009
Alpha amylase activities	Wheat	Hyperspectral imaging	1000–2500	PLSR	$R_c^2 = 0.72–0.88$	Xing *et al.*, 2011
Alpha amylase activities	Wheat	Spectroscopy	1000–2500	PLSR	$R_p^2 = 0.63–0.82$	Xing *et al.*, 2011
Protein	Wheat	Hyperspectral imaging	960–1700	PLSR, PCR	$R_p = 0.68, 0.82$	Mahesh *et al.*, 2011a
Alpha amylase	Wheat	Hyperspectral imaging	1255–2300	PCA, PLSR	$R_p^2 = 0.54, 0.73$	Xing *et al.*, 2009
Moisture	Wheat	Hyperspectral imaging	960–1700	PCA, LDA, QDA	61–100%	Mahesh *et al.*, 2011b

maize (Hao *et al.*, 2012), the phenol content of rapeseed (Bala and Singh, 2013) and the polyphenol content of cocoa beans (Sunoj *et al.*, 2016). In recent years, hyperspectral imaging has been used to predict the moisture content of corn (Cogdill *et al.*, 2004; Mahesh *et al.*, 2011b) and soybean during drying (Huang *et al.*, 2014), the sweetness (sucrose, glucose and fructose contents) of soybean (Monteiro *et al.*, 2007) and the colour of soybeans during drying (Huang *et al.*, 2014).

Quality assessment of seeds: insect damage and diseases

Seed damage by insects, fungi or natural causes, such as germination, are an important factor in seed quality during storage and processing. Seed damage is therefore taken seriously by consumers and the food industry. Various non-destructive techniques such as machine vision, spectroscopy, hyperspectral imaging, soft X-ray imaging, electronic nose and thermal imaging have been widely used in the detection of insect damage, insect infestation and diseases in seeds (Table 2). Machine vision has been used together with back-propagation neural networks based on colour features to detect external defects in rice seeds, such as germs, diseases and incompletely closed glumes, with an accuracy of 98.6–99.2% (Cheng *et al.*, 2006). A machine vision system developed for the detection of damaged wheat kernels based on morphological and textural properties was shown to have a classification accuracy of 91–94% (Delwiche *et al.*, 2013). A machine vision system was also used to detect damaged soybeans based on colour features with an accuracy of 99.6% (Shatadal and Tan, 2003). Recently, spectroscopy has been used to identify defects in corn (Esteve Agelet *et al.*, 2012) and soybean (Sirisomboon *et al.*, 2009). Hyperspectral imaging has been used to detect sprout damage in wheat (Singh *et al.*, 2009a; Xing *et al.*, 2010) and to detect sprouting in barley (Arngren *et al.*, 2011). In a recent study, a machine vision system was used to detect diseases and insects for the purpose of quality sorting of areca nuts with an accuracy of 90.9% (Huang, 2012). Spectroscopy-based methods have also been used to detect and classify fungus-infected maize (Giacomo and Stefania, 2013), wheat (Soto-Cámara *et al.*, 2012) and soybeans (Wang *et al.*, 2004), to determine the percentage of fungal infection in rice (Sirisomboon *et al.*, 2013) and to identify the green mottle mosaic virus in cucumber (Lee *et al.*, 2016). However, this technique has yielded unsatisfactory results for fungal infection determination in rice because the moisture and starch contents in rice affect the overall extent of fungal infection (Sirisomboon *et al.*, 2013). Numerous studies have been conducted using hyperspectral imaging to detect fungal-infected wheat (Singh *et al.*, 2012) and maize

Table 2. Assessment of insect damages and diseases in seeds using different non-destructive techniques

Insect damage/diseases	Seed	Method	Feature(s)/spectra region (nm)	Analysis method(s)	Result	References
Disease detection	Areca nuts	Machine vision	Geometric, colour	BPNN	90.90%	Huang, 2012
Sprout detection	Barley	Hyperspectral imaging	1002–1626	PCA, NNN, MLMR	Error: 3%, 32%	Arngren *et al.*, 2011
Damaged detection	Corn	Spectroscopy	850–1650	PLSDA, SIMCA, KNN, LS-SVM	<99%	Esteve Agelet *et al.*, 2012a
Aflatoxin B1	Corn	Hyperspectral imaging	1100–1700	PLS-DA	96.90%	Kandpal *et al.*, 2015
Green mottle mosaic virus	Cucumber	Raman Spectroscopy	400–1800 cm^{-1}	PLS-DA	86%	Lee *et al.*, 2016a
Fungal infection	Maize	Hyperspectral imaging	400–1000	PCA, DA	–	Del Fiore *et al.*, 2010
Fumonisins detection	Maize	Spectroscopy	650–2500	MLR	$R_p^2 = 0.91$	Giacomo and Stefania, 2013
Fungus-infect	Maize	Spectroscopy & color imaging	904–1685	LDA, ANN	89%, 79%	Tallada *et al.*, 2011
Aflatoxin B1	Maize	Hyperspectral imaging	1000–2500	PCA, FDA	88–100%	Wang *et al.*, 2014
Fungal infection	Maize	Hyperspectral imaging	1000–2498	PCA, PLSR	$R_p^2 = 0.73–0.86$	Williams *et al.*, 2012
Fungal infection	Maize	Hyperspectral imaging	400–700	LDA	94.4%, 91.7%	Yao *et al.*, 2013
Insect-damaged	Mungbean	Hyperspectral imaging	1000–1600	PCA, LDA, QDA	85%, 88%	Kaliramesh *et al.*, 2013
Defect detection	Rice	Machine vision	Contour, colour	PCA, BPNN	91.1–99.4%	Cheng *et al.*, 2006
Fungal infection	Rice	Spectroscopy	950–1650	PLSR	$R = 0.67$	Sirisomboon *et al.*, 2013
Insect-damaged	Soybean	Hyperspectral imaging	900–1700	PCA, LDA, QDA	40–94%	Chelladurai *et al.*, 2014
Insect-damaged	Soybean	Hyperspectral imaging	400–1000	KS, SVDD	95.60%	Huang *et al.*, 2013
Bug damage	Soybean	Soft X-ray imaging	Intensity of X-ray image	–	Good	Pinto *et al.*, 2009
Damaged detection	Soybean	Machine vision	Colour	ANN	99.60%	Shatadal and Tan, 2003
Defect detection	Soybean	Spectroscopy	600–1100	PCA, PLSDA, SIMCA	72.2%, 100%	Sirisomboon *et al.*, 2009
Fungal-damaged	Soybean	Spectroscopy	400–1700	PLS, ANN	84–100%	Wang *et al.*, 2004
Bacteria infected	Watermelon	Hyperspectral Imaging	400–1000	PLS-DA, LS-SVM	91.7%, 90.5%	Lee *et al.*, 2016b
Fusarium detection	Wheat	Hyperspectral imaging	400–1000	PCA, SAM	67%	Bauriegel *et al.*, 2011
Insect fragments	Wheat	Hyperspectral imaging	1000–1600	PLSR	$R_p = 0.99$	Bhuvaneswari *et al.*, 2011
Fungal infection	Wheat	Thermal imaging	–	LDA, QDA	96–100%	Chelladurai *et al.*, 2010
Fungal infection	Wheat	Hyperspectral imaging	400–1700	LDA	95%	Delwiche *et al.*, 2011
Damaged detection	Wheat	Machine vision	Morphology, texture	LDA, KNN	91–94%	Delwiche *et al.*, 2013
Insect infestation	Wheat	Soft X-ray imaging	Textural, shape moments, histogram	BPNN	98%	Karunakaran *et al.*, 2004
Insect infestation	Wheat	Soft X-ray imaging	Textural, histogram	BPNN	86%	Karunakaran *et al.*, 2004
Insect infestation	Wheat	Thermal imaging	–	LSD	83%	Manickavasagan *et al.*, 2008
Fungal detection	Wheat	Electronic nose	–	PCA, PLS-DA	85.30%	Paolesse *et al.*, 2006
Insect detection	Wheat	Hyperspectral imaging	1000–1700	PLS-DA, iPLS-DA	91–100%	Serranti *et al.*, 2013

Continued

Table 2. *Continued*

Insect damage/diseases	Seed	Method	Feature(s)/spectra region (nm)	Analysis method(s)	Result	References
Fusarium damaged detection	Wheat	Hyperspectral imaging	400–1000	PCA, LDA	92%	Shahin and Symons, 2011
Mildew-damaged	Wheat	Hyperspectral imaging	400–1000	PLSR	96%	Shahin *et al*., 2014
Sprout damaged	Wheat	Hyperspectral imaging	1000–1600	PCA, LDA, QDA, MD	100%	Singh *et al*., 2009a
Midge-damaged	Wheat	Hyperspectral imaging	700–1100	PCA, LDA, QDA	95.3–99.3%	Singh *et al*., 2010
Insect identification	Wheat	Hyperspectral imaging	700–1100	PCA, ANN, QDA	91–100%	Singh *et al*., 2010
Insect-damaged	Wheat	Hyperspectral imaging	1000–1600	LDA, QDA, MD	85–100%	Singh *et al*., 2009b
Fungal-damaged	Wheat	Hyperspectral imaging	700–1100	LDA, QDA, MD	97.3–100%	Singh *et al*., 2012
Fungicide detection	Wheat	Spectroscopy	400–2500	PCA, MPLS	84%	Soto-Cámara *et al*., 2012
Sprout-damaged	Wheat	Hyperspectral imaging	400–1000	PCA	88–100%	Xing *et al*., 2010
Sprout detection	Wheat	Soft X-ray imaging	–	ANN	90–95%	Neethirajan *et al*., 2007

(Del Fiore *et al*., 2010; Williams *et al*., 2012; Yao *et al*., 2013) and to detect bacteria-infected watermelon seeds (Lee *et al*., 2016). One study showed that the electronic nose is a powerful tool for the detection of fungal contamination in wheat; the accuracy obtained using partial least-squares discriminant analysis (PLS-DA) was found to be 85.3% (Paolesse *et al*., 2006). Recently, chlorophyll fluorescence has been used to sort white cabbage seeds, resulting in 97% germination by removing 13.2% of the seeds with very high chlorophyll fluorescence signal from the seed lot (Jalink *et al*., 1998). Similar studies have been conducted to evaluate the seed maturity in cabbage (Dell'Aquila *et al*., 2002), tomato (Jalink *et al*., 1999), barley (Konstantinova *et al*., 2002), carrot (Groot *et al*., 2006) and pepper (Kenanoglu *et al*., 2013) using chlorophyll fluorescence. Thermal imaging has been used to detect fungal infestations in stored wheat using linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA), with an accuracy of 100% for healthy samples and 96–97% for infected samples (Chelladurai *et al*., 2010). In a study in which a hyperspectral imaging system (1100–1700 nm) was used to detect aflatoxin B1 (AFB1) contaminants on corn kernels, a PLS-DA was performed, and a minimum classification accuracy of 96.9% was achieved (Kandpal *et al*., 2015). Similar studies have been performed to detect AFB1 contaminants on the surfaces of healthy maize kernels using a short wavelength infrared (SWIR) hyperspectral imaging system (Wang *et al*., 2014). The feasibility of short-wave near-infrared hyperspectral (700–1100 nm wavelength range) and digital colour imaging with different statistical discriminant classifiers was investigated for use in the detection of wheat damaged by four different insect species: the rice weevil (*Sitophilus oryzae*), the lesser grain borer (*Rhyzopertha dominica*), the rusty grain beetle (*Cryptolestes ferrugineus*) and the red flour beetle (*Tribolium castaneum*). Accuracies of 96% were achieved for healthy wheat kernels and 91–100% for insect-damaged wheat kernels (Singh *et al*., 2010a). Similarly, numerous studies have been performed to detect insect-damaged (Singh *et al*., 2009a, 2009b, 2010a, 2010b; Serranti *et al*., 2013) and mildew-damaged (Shahin *et al*., 2014) wheat using hyperspectral imaging. Hyperspectral imaging has also been used to detect insect-damaged mung bean (Kaliramesh *et al*., 2013) and insect fragments in semolina (Bhuvaneswari *et al*., 2011) and soybean (Huang *et al*., 2013; Chelladurai *et al*., 2014). Soft X-ray imaging technology has been used to detect red flour beetle infestation in wheat. An accuracy of 86% was achieved using textural features with a back-propagation neural network (BPNN) classifier (Karunakaran *et al*., 2004b). Soft X-ray imaging has also been used to detect internal wheat seed infestation by insects (Karunakaran *et al*., 2004a) and bug damage in soybean seeds (Pinto *et al*., 2009). In a recent study, thermal

https://doi.org/10.1017/S0960258516000234 Published online by Cambridge University Press

imaging was used to detect insect infestation in wheat with an accuracy of 77.6% for infested seeds and 83% for healthy seeds (Manickavasagan *et al.*, 2008). A recent study has shown that multispectral imaging can be used for spinach seeds to discriminate uninfected seeds from infected seeds with 80–100% classification rate (Olesen *et al.*, 2011).

Quality assessment of seeds: variety identification and classification

Variety identification and classification of seed species using non-destructive techniques has been extensively investigated by researchers worldwide (Table 3). Machine vision has been used to identify four wheat varieties using morphological features and colour features with an accuracy of 95.86%, which suggests that morphological features are more effective than colour features in recognizing wheat varieties (Arefi *et al.*, 2011). Machine vision has also been used to classify seeds of various species using morphological, colour, textural and wavelet features and to distinguish among species of wheat, barley, oats and rye (Choudhary *et al.*, 2008) and between wheat and barley (Guevara-Hernandez and Gomez-Gil, 2011). Similarly, machine vision has been used to identify nine Iranian wheat seeds based on their varieties, using textural features, with an accuracy of 98.15% (Pourreza *et al.*, 2012) and to recognize five Chinese corn varieties based on their external features (Chen *et al.*, 2010). Machine vision has also been used to identify bean varieties (Venora *et al.*, 2009), discriminate among wheat grain varieties (Zapotoczny, 2011a, 2011b), identify wheat varieties (Zayas *et al.*, 1986; Dubey *et al.*, 2006), classify corn (Jingtao *et al.*, 2012; Pazoki *et al.*, 2013), discriminate among rapeseed varieties (Li *et al.*, 2007; Kurtulmuş and Ünal 2015), classify pepper seeds (Kurtulmuş *et al.*, 2016) and classify rice varieties (Rad *et al.*, 2011; Hong *et al.*, 2015). Accuracy is an important evaluation parameter in variety identification; most of these studies have reported highly accurate results, in the range of 85–100%. In addition, machine vision has been shown to exhibit an overall accuracy of greater than 80% in grading maize (Yi *et al.*, 2007; Wu *et al.*, 2013) and soybean (Kılıç *et al.*, 2007). Recently, an electronic nose was used to distinguish among varieties of wheat seeds with an accuracy of 100% (Zhou *et al.*, 2012). Thermal imaging was used in a recent study to identify eight western Canadian wheat varieties. The overall classification accuracies of eight-class model, red-class model (four classes), white-class model (four classes), and pairwise (two-class) model comparisons obtained using a quadratic discriminant method were 76, 87, 79 and 95%, respectively, and those obtained using bootstrap and leave-one-out validation methods were 64, 87, 77 and 91%, respectively (Manickavasagan *et al.*, 2010). Hyperspectral imaging systems have been used for accurate and reliable discrimination among varieties of maize seeds (Zhang *et al.*, 2012), for classification of four varieties of maize seeds in different years (Huang *et al.*, 2016), for identification of wheat varieties (Choudhary *et al.*, 2009; Zhu *et al.*, 2012), for differentiation of wheat classes grown in western Canada (Mahesh *et al.*, 2008) and for differentiation among varieties of rice (Kong *et al.*, 2013). Some of these applications have achieved a classification accuracy of 100%. Hyperspectral imaging has also been used by several researchers for hardness classification of maize (Williams *et al.*, 2009; McGoverin *et al.*, 2011). Recently, hyperspectral imaging has been used to distinguish among transgenic soybeans (Esteve Agelet *et al.*, 2012) and rice (Liu *et al.*, 2014). Similarly, a NIRS technique has been used to distinguish among herbicide-resistant genetically modified soybean seeds (Lee and Choung, 2011). It has also been demonstrated that multispectral imaging technique can be used to distinguish transgenic- from non-transgenic rice seeds (Liu *et al.*, 2014).

Quality assessment of seeds: seed viability

A good-quality seed is one that is capable of germination under various conditions. A non-viable seed is one that fails to germinate even under optimal conditions (Bradbeer, 1988). In recent years, non-destructive techniques, mainly spectroscopy and hyperspectral imaging, have been widely used to predict seed viability (Table 4). A machine vision system was used to predict alfalfa and sativa seed germinability using the RGB (red, green, blue) density value with correlation coefficients of 0.982 and 0.984 for alfalfa and sativa, respectively (Behtari *et al.*, 2014). Researchers have also studied soybean and snap bean seed germinability using electric impedance spectroscopy in the frequency range of 60 Hz to 8 MHz (Vozáry *et al.*, 2007). Recently, spectroscopy has been used to distinguish viable gourd (Min and Kang, 2003), cucumber (Mo *et al.*, 2012), patula pine (Tigabu and Odén, 2003), watermelon and pepper seeds (Lohumi *et al.*, 2013; Seo *et al.*, 2016) from their non-viable counterparts, to assess corn seed viability (Ambrose *et al.*, 2016) and to predict the viability of cabbage and radish seeds (Shetty *et al.*, 2011). Most of these studies have reported accuracies of more than 90% in viable seed identification. Hyperspectral imaging systems have also been used for accurate and reliable discrimination of viable and non-viable seeds of corn (Ambrose *et al.*, 2016), radish (Ahn *et al.*, 2012), watermelon (Bae *et al.*, 2016) and pepper (Mo *et al.*, 2014) with accuracies of 95.6, 95, 84.2 and 99.4%, respectively. Recently, a hyperspectral fluorescence imaging technique was used to extract the

Table 3. Assessment of variety identification and classification in seeds using different non-destructive techniques

Variety classification/ identification	Seed	Method	Feature(s)/spectra region (nm)	Analysis method(s)	Result	References
Grading	Bean	Machine vision	Size, colour	ANN	69.1–99.3%	Kılıç *et al.*, 2007
Variety identification	Bean	Machine vision	Morphology	LDA	82.4–100%	Venora *et al.*, 2009
Variety classification	Corn	Machine vision	Morphology, colour, shape	MLP and Neuro-Fuzzy	94%, 96%	Pazoki *et al.*, 2013
Variety identification	Corn	Machine vision	Morphology, colour	SVM	97.3–98%	Jingtao *et al.*, 2012
Grading	Maize	Machine vision	Morphology	–	81.9%	Yi *et al.*, 2007
Variety identification	Maize	Machine vision	Geometric, shape, colour	BPNN	88–100%	Chen *et al.*, 2010
Grading	Maize	Machine vision	Colour		95%	Wu *et al.*, 2013
Varieties identification	Maize	Hyperspectral imaging	380–1030	PCA, KPCA, LS-SVM, ANN	98.89%	Zhang *et al.*, 2012
Hardness	Maize	Hyperspectral imaging	1000–2500	PCA	$R_p = 0.11–0.60$	McGoverin and Manley, 2012
Hardness	Maize	Hyperspectral imaging	960–2498	PCA, PLSDA	RMSEP = 0.18, 0.29	Williams *et al.*, 2009
Varieties classification	Maize	Hyperspectral imaging	400–1000	LS-SVM	94.40%	Huang *et al.*, 2016
Varieties discrimination	Pepper	Machine vision	Colour, shape and texture	ANN	84.94%	Kurtulmuş *et al.*, 2016
Variety classification	Rapeseed	Machine vision	Colour	ANN	92.06–100%	Li *et al.*, 2007
Varieties discrimination	Rapeseed	Machine vision	Colour, texture	SVM, KNN	99.24%	Kurtulmuş and Ünal, 2015
Varieties classification	Rice	Machine vision	Colour, texture	ANN	96.67%	Rad *et al.*, 2011
GM, non-GM	Rice	Hyperspectral imaging	405–970	PCA, PLSDA, LS-SVM, PCA-ANN	94–100%	Liu *et al.*, 2014
Variety identification	Rice	Hyperspectral imaging	1039–1612	PLSDA, SIMCA, RF, KNN, SVM, PCA	80–100%	Kong *et al.*, 2013
Varieties classification	Rice	Machine vision	Morphological, colour, texture	KNN, SVM, RF	90.54%	Hong *et al.*, 2015
GM, non-GM	Soybean	Hyperspectral imaging	880–1720	LW-PCR, PCA-ANN	72–79%	Esteve Agelet *et al.*, 2012b
GM, non-GM	Soybean	Spectroscopy	400–2500	PCA, PLSDA, SIMCA	97%	Lee and Choung, 2011
Classification	Wheat	Machine vision	Morphology, colour	ANN	95.86%	Arefi *et al.*, 2011
Classification	Wheat	Machine vision	Texture	LDA	98.15%	Pourreza *et al.*, 2012
Varieties discrimination	Wheat	Machine vision	Geometric		99–100%	Zapotoczny, 2011b
Variety identification	Wheat	Machine vision	Shape, size	ANN	84–94%	Dubey *et al.*, 2006
Varieties discrimination	Wheat	Machine vision	Texture	PCA, LDA, NDA, ANN	98%	Zapotoczny, 2011a
Variety identification	Wheat	Hyperspectral imaging	850–1700	PCA, SIMCA	90–100%	Zhu *et al.*, 2012
Varieties discrimination	Wheat	Electronic nose	–	PCA, LDA, BPNN	100%	Zhou *et al.*, 2012
Varieties discrimination	Wheat	Thermal imaging	–	QDA	64–95%	Manickavasagan *et al.*, 2010

Table 3. *Continued*

Variety classification/identification	Seed	Method	Feature(s)/spectra region (nm)	Analysis method(s)	Result	References
Varieties discrimination	Wheat	Hyperspectral imaging	960–1700	LDA, QDA, ANN	96–100%	Mahesh *et al.*, 2008
Variety identification	Wheat	Hyperspectral imaging	960–1700	PCA, LDA, QDA, ANN	79.9–99.1%	Choudhary *et al.*, 2009
Classification	Wheat, barley	Machine vision	Morphology, colour, texture	DA, KNN	55–100%	Guevara-Hernandez and Gomez-Gil, 2011
Classification	Wheat, barley, oats, rye	Machine vision	Morphology, colour, texture	LDA, QDA	89.4–99.4%	Choudhary *et al.*, 2008

fluorescence spectra of cucumber seeds in the 425–700 nm range to discriminate between viable and non-viable cucumber seeds using four types of algorithms. The discrimination accuracies achieved based on the subtraction image, the ratio image and the ratio-subtraction image were 100 and 99.0% for viable and non-viable seeds, respectively (Mo *et al.*, 2015). Hyperspectral imaging has also been used to classify muskmelon seeds based on germination ability with an accuracy of 94.6%, using a PLS-DA classification algorithm (Kandpal *et al.*, 2016). Hyperspectral imaging in the range of 1000–2498 nm was able to predict the viability of barley, wheat and sorghum seed with correlation coefficients of 0.85, 0.92 and 0.87, respectively (McGoverin *et al.*, 2011). Recently, multispectral imaging has been demonstrated to be a potential technique to evaluate castor seed viability with 96% correct classification rate at 19 different wavelengths ranging from 375 to 970 nm (Olesen *et al.*, 2015). Other studies have been conducted, using multispectral imaging to examine germination ability and germ length in spinach seeds; with the use of PLS-DA of images of spinach seeds it was possible to classify large spinach seeds from small-sized and medium-sized seeds (Shetty *et al.*, 2012). Infrared thermography has also been used to predict whether a quiescent seed will germinate or die upon water uptake, and the technique was reported to be able to detect imbibition- and germination-associated biophysical and biochemical changes (Kranner *et al.*, 2010). A similar technique has been used for viability evaluation of lettuce seeds (Kim *et al.*, 2013) and to evaluate germination capacity of leguminous plant seeds (Baranowski *et al.*, 2003).

Summary and future trends

This paper provided an overview of previous studies on seed quality assessment using non-destructive measurement techniques, namely chemical composition (Table 1), insect damage and diseases (Table 2), variety identification and classification (Table 3) and viability (Table 4). Machine vision, spectroscopy, hyperspectral imaging, thermal imaging, electronic nose and soft X-ray imaging are the main techniques to determine seed quality. Among them, spectroscopy and hyperspectral imaging techniques for chemical composition, machine vision, hyperspectral imaging, spectroscopy and soft X-ray imaging for insect and diseases detection, machine vision, thermal imaging and hyperspectral imaging for seed variety identification and classification, and spectroscopy and hyperspectral imaging for viability of seeds has been widely used in research, quality assessment, and for industrial purposes. For this, numerous spectroscopy instruments are commercially available. However, most of the

https://doi.org/10.1017/S0960258516000234 Published online by Cambridge University Press

Table 4. Assessment of seed viability using different non-destructive techniques

Application	Seed	Method	Feature(s)/spectra region (nm)	Analysis method(s)	Result	References
Classify based on germination ability	Muskmelon	Hyperspectral imaging	948–2494	PLS-DA	94.60%	Kandpal *et al.*, 2016
Classify the viable and non-viable seeds	Gourd	Spectroscopy	1100–2500	PLS-DA	96%, 95%	Min and Kang, 2003
Classify the viable and non-viable seeds	Cucumber	Raman spectroscopy	150–1890 cm^{-1}	PLS-DA	100%	Mo *et al.*, 2012
Classify the viable and non-viable seeds	Watermelon	Hyperspectral Imaging	1000–2500	PLS-DA	84.20%	Bae *et al.*, 2016
Discriminate the viable and empty seeds	*Patula* pine	Spectroscopy	400–2498	PLS model	96%, 88%	Tigabu and Odén, 2003
Discriminate the viable and non-viable seeds	Corn	Hyperspectral Imaging	1000–2500	PLS-DA	95.60%	Ambrose *et al.*, 2016b
Discriminate the viable and non-viable seeds	Radish	Hyperspectral Imaging	400–1000	PLS-DA	95%	Ahn *et al.*, 2012
Discriminate the viable and non-viable seeds	Pepper	Hyperspectral Imaging	400–700	PLS-DA	99.4%	Mo *et al.*, 2014
Discriminate the viable and non-viable seeds	Watermelon	FT-NIR spectroscopy	1000–2500	PLS-DA	100%	Lohumi *et al.*, 2013
Discriminate the viable and non-viable seeds	Cucumber	Hyperspectral fluorescence imaging	425–700	SWI	99%, 97%	Mo *et al.*, 2015
Discriminate the viable and non-viable seeds	Pepper	FT-NIR spectroscopy, Raman spectroscopy	1400–2400, 1800–970 cm^{-1}	PLS-DA	99%	Seo *et al.*, 2016
Measure the seed viability	Corn	FT-NIR spectroscopy, Raman spectroscopy	1000–2500, 170–3200 cm^{-1}	PCA, PLS-DA	100%	Ambrose *et al.*, 2016a
Predict the viability of seeds	Barley, wheat, sorghum	Hyperspectral Imaging	1000–2498	PCA, PLS-DA	$R = 0.85, 0.92, 0.87$	McGoverin *et al.*, 2011
Predict the viability of seeds	Cabbage, radish	Spectroscopy	1100–2500	ECVA, iECVA	Error: 6–8%, 2–3%	Shetty *et al.*, 2011
Predicting the seed germinability	Alfalfa, *Sativa*	Machine vision	RGB density value	–	$R = 0.982, 0.984$	Behtari *et al.*, 2014
Predicting the seed germinability	Soybean, snap bean	Electrical impedance spectroscopy	60 Hz–8 MHz	–	$R^2 = 0.27–0.49, 0.44–0.50$	Vozáry *et al.*, 2007

instruments are too expensive to be widely used in practical production. Therefore, one of the main concerns of current researchers is how to decrease the cost while maintaining accuracy of analysis. In contrast, hyperspectral imaging provides both spatial and spectral information and is suitable for both external quality classification and for prediction of internal chemical composition. However, current hyperspectral imaging technology is not widely used compared with spectroscopy. This limitation may be due to the time-consuming process of hyperspectral imaging to generate a hypercube and the large amount of hyperspectral data. As a new technology that has only been studied for over a decade, hyperspectral imaging has a long way to go before it can be moved from laboratories to practical application. Recently, machine vision techniques have been placed as in-line detection and grading systems in actual production. Generally, a complete detection process for machine vision technique includes image acquisition, image processing and analysis, and formulation of decisions. These steps can be accomplished with only one smart camera, considering the increasing development of electronics and microprocessors. Thermal imaging and soft X-ray imaging are of very limited use in seed quality assessment due to high cost, the requirement of a controlled environment as the precision of this instrument fluctuates with environmental condition. The electronic nose technique is commonly used to determine seed quality during storage because it detects chemical interactions between the substrates over the gas sensors and the aromatic compounds. Electronic noses today generally suffer from significant weaknesses which limit their widespread application in seed quality assessment. Their sensing ability is profoundly influenced by ambient factors that are very critical in seed quality assessment. We should address the rapid development of instruments coupled with the improvement of analysis algorithms to help to promote efficient technologies for the seed quality assessment field.

Conclusions

This paper presents an overview of studies that have shown that non-destructive techniques can be used effectively as reliable and accurate tools for the composition prediction, variety identification and classification, quality grading, damage detection, insect infestation detection and viability and germinability prediction of agricultural seeds. These non-destructive techniques are rapid, accurate, reliable and simple tools for quality assessment of seeds. Given the urgent need of the industry for advanced testing methods and rapid development of suitable technologies and instruments, non-destructive techniques exhibit great potential to be dominant methods for quality assessment of seeds.

Acknowledgements

None.

Financial support

This research was partially supported by the Export Strategy Technology Development Program, Ministry of Agriculture, Food and Rural Affairs (MAFRA) and by Golden Seed Project, MAFRA, Ministry of Oceans and Fisheries (MOF), Rural Development Administration (RDA) and Korea Forest Service (KFS), Republic of Korea.

Conflicts of interest

None.

References

Ahn, C.K., Mo, C.Y., Kang, J.-S. and Cho, B.-K. (2012) Non-destructive classification of viable and non-viable radish (Raphanus sativus L.) seeds using hyperspectral reflectance imaging. *Journal of Biosystems Engineering* **37**, 411–419.

Ambrose, A., Lohumi, S., Lee, W.-H.H. and Cho, B.K. (2016a) Comparative non-destructive measurement of corn seed viability using Fourier transform near-infrared (FT-NIR) and Raman spectroscopy. *Sensors and Actuators B: Chemical* **224**, 500–506.

Ambrose, A., Kandpal, L.M., Kim, M.S., Lee, W.-H. and Cho, B.-K. (2016b) High speed measurement of corn seed viability using hyperspectral imaging. *Infrared Physics & Technology* **75**, 173–179.

Arefi, A., Motlagh, A.M. and Teimourlou, R.F. (2011) Wheat class identification using computer vision system and artificial neural networks. *International Agrophysics* **25**, 319–323.

Armstrong, P.R., Tallada, J.G., Hurburgh, C.R., Hildebrand, D.F. and Specht, J.E. (2011) Development of single-seed near-infrared spectroscopic predictions of corn and soybean constituents using bulk reference values and mean spectra. *Transactions of the ASABE* **54**, 1529–1535.

Arngren, M., Hansen, P.W., Eriksen, B., Larsen, J. and Larsen, R. (2011) Analysis of pregerminated barley using hyperspectral image analysis. *Journal of Agricultural and Food Chemistry* **59**, 11385–11394.

Bae, H., Seo, Y.-W., Kim, D.-Y., Lohumi, S., Park, E. and Cho, B.-K. (2016) Development of non-destructive sorting technique for viability of watermelon seed by using hyperspectral image processing. *Journal of the Korean Society for Non-destructive Testing* **36**, 35–44.

Bala, M. and Singh, M. (2013) Non-destructive estimation of total phenol and crude fiber content in intact seeds of rapeseed–mustard using FTNIR. *Industrial Crops and Products* **42**, 357–362.

Baranowski, P., Mazurek, W. and Walczak, R.T. (2003) The use of thermography for pre-sowing evaluation of seed germination capacity. *Acta Horticulturae* **604**, 459–465.

Bauriegel, E., Giebel, A., Geyer, M., Schmidt, U. and Herppich, W.B.B. (2011) Early detection of *Fusarium* infection in wheat using hyper-spectral imaging. *Computers and Electronics in Agriculture* **75**, 304–312.

Baye, T. and Becker, H.C. (2004) Analyzing seed weight, fatty acid composition, oil, and protein contents in *Vernonia galamensis* germplasm by near-infrared reflectance spectroscopy. *Journal of the American Oil Chemists' Society* **81**, 641–645.

Baye, T.M., Pearson, T.C. and Settles, A.M. (2006) Development of a calibration to predict maize seed composition using single kernel near infrared spectroscopy. *Journal of Cereal Science* **43**, 236–243.

Behtari, B., De Luis, M. and Dabbagh Mohammadi Nasab, A. (2014) Predicting germination of *Medicago sativa* and *Onobrychis viciifolia* seeds by using image analysis. *Turkish Journal of Agriculture and Forestry* **38**, 615–623.

Bhuvaneswari, K., Fields, P.G., White, N.D.G., Sarkar, A.K., Singh, C.B. and Jayas, D.S. (2011) Image analysis for detecting insect fragments in semolina. *Journal of Stored Products Research* **47**, 20–24.

Bradbeer, J.W. (1988) *Seed Dormancy and Germination*. Boston, MA, Springer US).

Cantarelli, M.A., Funes, I.G., Marchevsky, E.J. and Camiña, J.M. (2009) Determination of oleic acid in sunflower seeds by infrared spectroscopy and multivariate calibration method. *Talanta* **80**, 489–492.

Chelladurai, V., Jayas, D.S. and White, N.D.G. (2010) Thermal imaging for detecting fungal infection in stored wheat. *Journal of Stored Products Research* **46**, 174–179.

Chelladurai, V., Karuppiah, K., Jayas, D.S., Fields, P.G. and White, N.D.G. (2014) Detection of *Callosobruchus maculatus* (F.) infestation in soybean using soft X-ray and NIR hyperspectral imaging techniques. *Journal of Stored Products Research* **57**, 43–48.

Chen, G.L., Zhang, B., Wu, J.G. and Shi, C.H. (2011) Non-destructive assessment of amino acid composition in rapeseed meal based on intact seeds by near-infrared reflectance spectroscopy. *Animal Feed Science and Technology* **165**, 111–119.

Chen, H., Ai, W., Feng, Q., Jia, Z. and Song, Q. (2014) FT-NIR spectroscopy and Whittaker smoother applied to joint analysis of duel-components for corn. *Spectrochimica Acta Part A Molecular and Biomolecular Spectroscopy* **118**, 752–759.

Chen, J., Ren, X., Zhang, Q., Diao, X. and Shen, Q. (2013) Determination of protein, total carbohydrates and crude fat contents of foxtail millet using effective wavelengths in NIR spectroscopy. *Journal of Cereal Science* **58**, 241–247.

Chen, X., Xun, Y., Li, W. and Zhang, J. (2010) Combining discriminant analysis and neural networks for corn variety identification. *Computers and Electronics in Agriculture* **71**, S48–S53.

Cheng, F., Ying, Y.B. and Li, Y.B. (2006) Detection of defects in rice seeds using machine vision. *Transactions of the ASABE* **49**, 1929–1934.

Choudhary, R., Paliwal, J. and Jayas, D.S. (2008) Classification of cereal grains using wavelet, morphological, colour, and textural features of non-touching kernel images. *Biosystems Engineering* **99**, 330–337.

Choudhary, R., Mahesh, S., Paliwal, J. and Jayas, D.S. (2009) Identification of wheat classes using wavelet features from near infrared hyperspectral images of bulk samples. *Biosystems Engineering* **102**, 115–127.

Choung, M.-G. (2010) Determination of sucrose content in soybean using near-infrared reflectance spectroscopy. *Journal of the Korean Society for Applied Biological Chemistry* **53**, 478–484.

Cogdill, R.P., Hurburgh, C.R., Rippke, G.R., Bajic, S.J., Jones, R.W., McClelland, J.F., Jensen, T.C. and Liu, J. (2004) Single-kernel maize analysis by near-infrared hyperspectral imaging. *Transactions of the ASAE* **47**, 311–320.

Copeland, L.O. and McDonald, M.B. (1999) *Principles of Seed Science and Technology*. Boston, MA, Springer US).

Daun, J.K., Clear, K.M. and Williams, P. (1994) Comparison of three whole seed near-infrared analyzers for measuring quality components of canola seed. *Journal of the American Oil Chemists' Society* **71**, 1063–1068.

Dell'Aquila, A., van der Schoor, R. and Jalink, H. (2002) Application of chlorophyll fluorescence in sorting controlled deteriorated white cabbage (*Brassica oleracea* L.) seeds. *Seed Science and Technology* **30**, 689–695.

Delwiche, S.R., Kim, M.S. and Dong, Y. (2011) *Fusarium* damage assessment in wheat kernels by Vis/NIR hyperspectral imaging. *Sensing and Instrumentation for Food Quality and Safety* **5**, 63–71.

Delwiche, S.R., Yang, I.-C. and Graybosch, R.A. (2013) Multiple view image analysis of freefalling U.S. wheat grains for damage assessment. *Computers and Electronics in Agriculture* **98**, 62–73.

Dubey, B.P., Bhagwat, S.G., Shouche, S.P. and Sainis, J.K. (2006) Potential of artificial neural networks in varietal identification using morphometry of wheat grains. *Biosystems Engineering* **95**, 61–67.

Esteve Agelet, L., Ellis, D.D., Duvick, S., Goggi, A.S., Hurburgh, C.R. and Gardner, C.A. (2012a) Feasibility of near infrared spectroscopy for analyzing corn kernel damage and viability of soybean and corn kernels. *Journal of Cereal Science* **55**, 160–165.

Esteve Agelet, L., Gowen, A.A., Hurburgh, C.R. and O'Donell, C.P. (2012b) Feasibility of conventional and Roundup Ready® soybeans discrimination by different near infrared reflectance technologies. *Food Chemistry* **134**, 1165–1172.

Fassio, A. and Cozzolino, D. (2004) Non-destructive prediction of chemical composition in sunflower seeds by near infrared spectroscopy. *Industrial Crops and Products* **20**, 321–329.

Fassio, A., Fernández, E.G., Restaino, E.A., La Manna, A. and Cozzolino, D. (2009) Predicting the nutritive value of high moisture grain corn by near infrared reflectance spectroscopy. *Computers and Electronics in Agriculture* **67**, 59–63.

Ferreira, D.S., Pallone, J.A.L. and Poppi, R.J. (2013) Fourier transform near-infrared spectroscopy (FT-NIRS) application to estimate Brazilian soybean [*Glycine max* (L.) Merril] composition. *Food Research International* **51**, 53–58.

Ferreira, D.S., Galão, O.F., Pallone, J.A.L. and Poppi, R.J. (2014) Comparison and application of near-infrared (NIR) and mid-infrared (MIR) spectroscopy for determination of quality parameters in soybean samples. *Food Control* **35**, 227–232.

Del Fiore, A., Reverberi, M., Ricelli, A., Pinzari, F., Serranti, S., Fabbri, A.A., Bonifazi, G. and Fanelli, C. (2010) Early detection of toxigenic fungi on maize by hyperspectral imaging analysis. *International Journal of Food Microbiology* **144**, 64–71.

Giacomo, D.R. and Stefania, D.Z. (2013) A multivariate regression model for detection of fumonisins content in maize from near infrared spectra. *Food Chemistry* **141**, 4289–4294.

Groot, S.P.C., Birnbaum, Y., Rop, N., Jalink, H., Forsberg, G., Kromphardt, C., Werner, S. and Koch, E. (2006) Effect of seed maturity on sensitivity of seeds towards physical sanitation treatments. *Seed Science & Technology* **34**, 403–413.

Guevara-Hernandez, F. and Gomez-Gil, J. (2011) A machine vision system for classification of wheat and barley grain kernels. *Spanish Journal of Agricultural Research* **9**, 672.

Gunasekaran, S., Paulsen, M.R. and Shove, G.C. (1985) Optical methods for non-destructive quality evaluation of agricultural and biological materials. *Journal of Agricultural Engineering Research* **32**, 209–241.

Hacisalihoglu, G., Larbi, B. and Settles, A.M. (2010) Near-infrared reflectance spectroscopy predicts protein, starch, and seed weight in intact seeds of common bean (*Phaseolus vulgaris* L.). *Journal of Agricultural and Food Chemistry* **58**, 702–706.

Hao, X., Thelen, K. and Gao, J. (2012) Prediction of the ethanol yield of dry-grind maize grain using near infrared spectroscopy. *Biosystems Engineering* **112**, 161–170.

Hong, P.T.T., Hai, T.T.T., Lan, L.T., Hoang, V.T., Hai, V. and Nguyen, T.T. (2015) Comparative study on vision based rice seed varieties identification, pp. 377–382 in *Proceedings of the Seventh International Conference on Knowledge and Systems Engineering*, IEEE-CPS.

Hornberg, A. (2007) *Handbook of Machine Vision*. Wiley-VCH Verlag GmbH & Co KGaA.

Huang, K.-Y. (2012) Detection and classification of areca nuts with machine vision. *Computers & Mathematics with Applications* **64**, 739–746.

Huang, Z., Sha, S., Rong, Z., Chen, J., He, Q., Khan, D.M. and Zhu, S. (2013b) Feasibility study of near infrared spectroscopy with variable selection for non-destructive determination of quality parameters in shell-intact cottonseed. *Industrial Crops and Products* **43**, 654–660.

Huang, M., Tang, J., Yang, B. and Zhu, Q. (2016) Classification of maize seeds of different years based on hyperspectral imaging and model updating. *Computers and Electronics in Agriculture* **122**, 139–145.

Huang, M., Wan, X., Zhang, M. and Zhu, Q. (2013a) Detection of insect-damaged vegetable soybeans using hyperspectral transmittance image. *Journal of Food Engineering* **116**, 45–49.

Huang, M., Wang, Q., Zhang, M. and Zhu, Q. (2014) Prediction of color and moisture content for vegetable soybean during drying using hyperspectral imaging technology. *Journal of Food Engineering* **128**, 24–30.

Huang, M., Wang, Q.G., Zhu, Q.B., Qin, J.W. and Huang, G. (2015) Review of seed quality and safety tests using optical sensing technologies. *Seed Science & Technology* **43**, 337–366.

Hurburgh, C.R. (2007) Measurement of fatty acids in whole soybeans with near infrared spectroscopy. *Lipid Technology* **19**, 88–90.

Igne, B., Rippke, G.R. and Hurburgh Jr, C.R. (2008) Measurement of whole soybean fatty acids by near infrared spectroscopy. *Journal of the American Oil Chemists' Society* **85**, 1105–1113.

Ishimwe, R., Abutaleb, K. and Ahmed, F. (2014) Applications of thermal imaging in agriculture—a review. *Advances in Remote Sensing* **3**, 128–140.

Jalink, H., Frandas, A., Schoor, R. van der and Bino, J.B. (1998) Chlorophyll fluorescence of the testa of Brassica oleracea seeds as an indicator of seed maturity and seed quality. *Scientia Agricola* **55**, 88–93.

Jalink, H., van der Schoor, R., Birnbaum, Y.E. and Bino, R.J. (1999) Seed chlorophyll content as an indicator for seed maturity and seed quality. *Acta Horticulturae* **504**, 219–228.

Jingtao, J., Yanyao, W., Ranbing, Y. and Shuli, M. (2012) Variety identification of corn seed based on Bregman Split method. *Transactions from the Chinese Society of Agricultural Engineering* **28**, 248–252.

Kaliramesh, S., Chelladurai, V., Jayas, D.S., Alagusundaram, K., White, N.D.G. and Fields, P.G. (2013) Detection of infestation by *Callosobruchus maculatus* in mung bean using near-infrared hyperspectral imaging. *Journal of Stored Products Research* **52**, 107–111.

Kandpal, L.M., Lee, S., Kim, M.S., Bae, H. and Cho, B.-K. (2015) Short wave infrared (SWIR) hyperspectral imaging technique for examination of aflatoxin B1 (AFB1) on corn kernels. *Food Control* **51**, 171–176.

Kandpal, L.M., Lohumi, S., Kim, M.S., Kang, J.-S. and Cho, B.-K. (2016) Near-Infrared hyperspectral imaging system coupled with multivariate methods to predict viability and vigor in muskmelon seeds. *Sensors and Actuators B: Chemical* **229**, 534–544.

Karunakaran, C., Jayas, D. and White, N.D. (2004a) Detection of internal wheat seed infestation by *Rhyzopertha dominica* using X-ray imaging. *Journal of Stored Products Research* **40**, 507–516.

Karunakaran, C., Jayas, D.S. and White, N.D.G. (2004b) Identification of wheat kernels damaged by the red flour beetle using x-ray images. *Biosystems Engineering* **87**, 267–274.

Kenanoglu, B.B., Demir, I. and Jalink, H. (2013) Chlorophyll fluorescence sorting method to improve quality of capsicum pepper seed lots produced from different maturity fruits. *Hortscience* **48**, 965–968.

Kılıç, K., Boyacı, İ.H., Köksel, H. and Küsmenoğlu, İ. (2007) A classification system for beans using computer vision system and artificial neural networks. *Journal of Food Engineering* **78**, 897–904.

Kim, G., Kim, G., Ahn, C.-K., Yoo, Y. and Cho, B.-K. (2013) Mid-infrared lifetime imaging for viability evaluation of lettuce seeds based on time-dependent thermal decay characterization. *Sensors* **13**, 2986–2996.

Kim, K.S., Park, S.H., Choung, M.G. and Jang, Y.S. (2007) Use of near-infrared spectroscopy for estimating fatty acid composition in intact seeds of rapeseed. *Journal of Crop Science and Biotechnology* **10**, 15–20.

Kong, W., Zhang, C., Liu, F., Nie, P. and He, Y. (2013) Rice seed cultivar identification using near-infrared hyperspectral imaging and multivariate data analysis. *Sensors* **13**, 8916–8927.

Konstantinova, P., Van Der Schoor, R., Van Den Bulk, R. and Jalink, H. (2002) Chlorophyll fluorescence sorting as a method for improvement of barley (*Hordeum vulgare* L.) seed health and germination. *Seed Science & Technology* **30**, 411–421.

Kovalenko, I. V., Rippke, G.R. and Hurburgh, C.R. (2006) Measurement of soybean fatty acids by near-infrared spectroscopy: Linear and nonlinear calibration methods. Journal of the American Oil Chemists' Society **83**, 421–427.

Kranner, I., Kastberger, G., Hartbauer, M. and Pritchard, H. W. (2010) Non-invasive diagnosis of seed viability using infrared thermography. *Proceedings of the National Academy of Sciences of the USA* **107**, 3912–3917.

Kurtulmuş, F. and Ünal, H. (2015) Discriminating rapeseed varieties using computer vision and machine learning. *Expert Systems with Applications* **42**, 1880–1891.

Kurtulmuş, F., Alibaş, İ. and Kavdir, I. (2016) Classification of pepper seeds using machine vision based on neural network. *International Journal of Agricultural and Biological Engineering* **9**, 51–62.

Lee, J.H. and Choung, M.-G. (2011) Non-destructive determination of herbicide-resistant genetically modified soybean seeds using near-infrared reflectance spectroscopy. *Food Chemistry* **126**, 368–373.

Lee, H., Cho, B.-K., Kim, M.S., Lee, W.-H., Tewari, J., Bae, H., Sohn, S.-I. and Chi, H.-Y. (2013) Prediction of crude protein and oil content of soybeans using Raman spectroscopy. *Sensors and Actuators B: Chemical* **185**, 694–700.

Lee, H., Lim, H.-S. and Cho, B.-K. (2016a) Classification of cucumber green mottle mosaic virus (CGMMV) infected watermelon seeds using Raman spectroscopy, p. 98640D in *Proceedings SPIE 9864, Sensing for Agriculture and Food Quality and Safety VIII* (*International Society for Optics and Photonics*). doi:10.1117/12.2228264

Lee, H., Kim, M.S., Song, Y.-R., Oh, C., Lim, H.-S., Lee, W.-H., Kang, J.-S. and Cho, B.-K. (2016b) Non-destructive evaluation of bacteria-infected watermelon seeds using Vis/NIR hyperspectral imaging. *Journal of the Science of Food and Agriculture*. doi: 10.1002/jsfa.7832

Li, J., Liao, G., Ou, Z. and Jin, J. (2007) Rapeseed seeds classification by machine vision, pp. 222–226 in *Workshop on Intelligent Information Technology Application (IITA 2007) IEEE*.

Liu, C., Liu, W., Lu, X., Chen, W., Yang, J. and Zheng, L. (2014) Non-destructive determination of transgenic *Bacillus thuringiensis* rice seeds (*Oryza sativa* L.) using multispectral imaging and chemometric methods. *Food Chemistry* **153**, 87–93.

Lohumi, S., Mo, C., Kang, J.-S., Hong, S.-J. and Cho, B.-K. (2013) Non-destructive evaluation for the viability of watermelon (*Citrullus lanatus*) seeds using fourier transform near infrared spectroscopy. *Journal of Biosystems Engineering* **38**, 312–317.

Lohumi, S., Lee, S., Lee, H. and Cho, B.-K. (2015) A review of vibrational spectroscopic techniques for the detection of food authenticity and adulteration. *Trends in Food Science and Technology* **46**, 85–98.

Mahesh, S., Manickavasagan, A., Jayas, D.S., Paliwal, J. and White, N.D.G. (2008) Feasibility of near-infrared hyperspectral imaging to differentiate Canadian wheat classes. *Biosystems Engineering* **101**, 50–57.

Mahesh, S., Jayas, D.S., Paliwal, J., and White, N.D.G. (2011a) Near-infrared hyperspectral imaging for protein and hardness predictions of bulk samples of western canadian wheat from different locations and crop years using multivariate regression models. In CSBE/SCGAB Annual Conference (Winnipeg, Manitoba).

Mahesh, S., Jayas, D.S., Paliwal, J. and White, N.D.G. (2011b) Identification of wheat classes at different moisture levels using near-infrared hyperspectral images of bulk samples. *Sensing and Instrumentation for Food Quality and Safety* **5**, 1–9.

Manickavasagan, A., Jayas, D.S. and White, N.D.G. (2008) Thermal imaging to detect infestation by *Cryptolestes ferrugineus* inside wheat kernels. *Journal of Stored Products Research* **44**, 186–192.

Manickavasagan, A., Jayas, D.S., White, N.D.G. and Paliwal, J. (2010) Wheat class identification using thermal imaging. *Food Bioprocessing and Technology* **3**, 450–460.

Mathanker, S.K., Weckler, P.R. and Bowser, T.J. (2013) X-ray applications in food and agriculture: a review. *Transactions of the ASABE* **56**, 1227–1239.

McGoverin, C.M., Engelbrecht, P., Geladi, P. and Manley, M. (2011) Characterisation of non-viable whole barley, wheat and sorghum grains using near-infrared hyperspectral data and chemometrics. *Analytical and Bioanalytical Chemistry* **401**, 2283–2289.

Min, T.G. and Kang, W.S. (2003) Non-destructive separation of viable and non-viable gourd (*Lagenaria siceraria*) seeds using single seed near infrared spectroscopy. *Journal of the Korean Society of Horticultural Science* **44**, 545–548.

Mo, C., Kang, S., Lee, K., Kim, G., Cho, B.-K., Lim, J.-G., Lee, H.-S. and Park, J. (2012) Germination prediction of cucumber (*Cucumis sativus*) seed using Raman spectroscopy. *Journal of Biosystems Engineering* **37**, 404–410.

Mo, C., Kim, G., Lee, K., Kim, M., Cho, B.-K., Lim, J. and Kang, S. (2014) Non-destructive quality evaluation of pepper (*Capsicum annuum* L.) seeds using led-induced hyperspectral reflectance imaging. *Sensors* **14**, 7489–7504.

Mo, C., Kim, M.S., Lim, J., Lee, K., Kim, G. and Cho, B.-K. (2015) Multispectral fluorescence imaging technique for discrimination of cucumber seed viability. *Transactions of the ASABE* **58**, 959–968.

Monteiro, S.T., Minekawa, Y., Kosugi, Y., Akazawa, T. and Oda, K. (2007) Prediction of sweetness and amino acid content in soybean crops from hyperspectral imagery. *ISPRS Journal of Photogrammetry and Remote Sensing* **62**, 2–12.

Moschner, C.R. and Biskupek-Korell, B. (2006) Estimating the content of free fatty acids in high-oleic sunflower seeds by near-infrared spectroscopy. *European Journal of Lipid Science and Technology* **108**, 606–613.

Neethirajan, S., Karunakaran, C., Symons, S. and Jayas, D. S. (2006) Classification of vitreousness in durum wheat using soft X-rays and transmitted light images. *Computers and Electronics in Agriculture* **53**, 71–78.

Neethirajan, S., Jayas, D.S. and White, N.D.G. (2007) Detection of sprouted wheat kernels using soft X-ray image analysis. *Journal of Food Engineering* **81**, 509–513.

Olesen, M., Nikneshan, P., Shrestha, S., Tadayyon, A., Deleuran, L., Boelt, B. and Gislum, R. (2015) Viability prediction of *Ricinus cummunis* L. *seeds using multispectral imaging*. Sensors **15**, 4592–4604.

Olesen, M.H., Carstensen, J.M.M. and Boelt, B. (2011) Multispectral imaging as a potential tool for seed health testing of spinach (*Spinacia oleracea* L.). *Seed Science & Technology* **39**, 140–150.

Pandord, J.A., Williams, P.C. and DeMan, J.M. (1988) Analysis of oilseeds for protein, oil, fiber and moisture by near-infrared reflectance spectroscopy. Journal of the American Oil Chemists' Society **65**, 1627–1634.

Paolesse, R., Alimelli, A., Martinelli, E., Natale, C. Di, D'Amico, A., D'Egidio, M.G., Aureli, G., Ricelli, A. and Fanelli, C. (2006) Detection of fungal contamination of cereal grain samples by an electronic nose. *Sensors and Actuators B: Chemical* **119**, 425–430.

Patil, A.G., Oak, M.D., Taware, S.P., Tamhankar, S.A. and Rao, V.S. (2010) Non-destructive estimation of fatty acid composition in soybean [*Glycine max* (L.) Merrill] seeds using near-infrared transmittance spectroscopy. *Food Chemistry* **120**, 1210–1217.

Pazoki, A., Farokhi, F. and Pazoki, Z. (2013) Corn seed varieties classification based on mixed morphological and color features using artificial neural networks. *Research Journal of Applied Sciences, Engineering and Technology* **6**, 3506–3513.

Pearson, T.C. and Wicklow, D.T. (2006) Detection of corn kernels infected by fungi. *Transactions of the ASABE* **49**, 1235–1245.

Pérez-Vich, B., Velasco, L. and Fernández-Martínez, J.M. (1998) Determination of seed oil content and fatty acid composition in sunflower through the analysis of intact seeds, husked seeds, meal and oil by near-infrared reflectance spectroscopy. *Journal of the American Oil Chemists' Society* **75**, 547–555.

Petisco, C., García-Criado, B., Vázquez-de-Aldana, B.R., de Haro, A. and García-Ciudad, A. (2010) Measurement of quality parameters in intact seeds of Brassica species using visible and near-infrared spectroscopy. *Industrial Crops and Products* **32**, 139–146.

Phan-Thien, K.-Y., Golic, M., Wright, G.C. and Lee, N.A. (2011) Feasibility of estimating peanut essential minerals by near infrared reflectance spectroscopy. *Sensing and Instrumentation for Food Quality and Safety* **5**, 43–49.

Pinto, T.L.F., Cicero, S.M., França-Neto, J.B. and Forti, V.A. (2009) An assessment of mechanical and stink bug damage in soybean seed using X-ray analysis test. *Seed Science & Technology* **37**, 110–120.

Plans, M., Simó, J., Casañas, F., Sabaté, J. and Rodriguez-Saona, L. (2013) Characterization of common beans (*Phaseolus vulgaris* L.) by infrared spectroscopy: Comparison of MIR, FT-NIR and dispersive NIR using portable and benchtop instruments. *Food Research International* **54**, 1643–1651.

Pourreza, A., Pourreza, H., Abbaspour-Fard, M.-H. and Sadrnia, H. (2012) Identification of nine Iranian wheat seed varieties by textural analysis with image processing. *Computers and Electronics in Agriculture* **83**, 102–108.

Qin, J., Chao, K., Kim, M.S. and Burks, T.F. (2013) Hyperspectral and multispectral imaging for evaluating food safety and quality. *Journal of Food Engineering* **118** (2), 157–171.

Rad, S.J.M., Tab, F.A. and Mollazade, K. (2011) Classification of rice varieties using optimal color and texture features and bp neural networks, pp. 1–5 in *7th Iranian Conference on Machine Vision and Image Processing* (IEEE).

Rosales, A., Galicia, L., Oviedo, E., Islas, C. and Palacios-Rojas, N. (2011) Near-infrared reflectance spectroscopy (NIRS) for protein, tryptophan, and lysine evaluation in quality protein maize (QPM) breeding programs. *Journal of Agricultural and Food Chemistry* **59**, 10781–10786.

Rudolphi, S., Becker, H.C., Schierholt, A. and von Witzke-Ehbrecht, S. (2012) Improved estimation of oil, linoleic and oleic acid and seed hull fractions in safflower by NIRS. Journal of the American Oil Chemists' Society **89**, 363–369.

Seo, Y.-W., Ahn, C.K., Lee, H., Park, E., Mo, C. and Cho, B. (2016) Non-destructive sorting techniques for viable pepper (*Capsicum annuum* L.) seeds using fourier transform near-infrared and Raman spectroscopy. *Journal of Biosystems Engineering* **41**, 51–59.

Serranti, S., Cesare, D. and Bonifazi, G. (2013) The development of a hyperspectral imaging method for the detection of *Fusarium*-damaged, yellow berry and vitreous Italian durum wheat kernels. *Biosystems Engineering* **115**, 20–30.

Shahin, M.A. and Symons, S.J. (2011) Detection of fusarium damaged kernels in Canada western red spring wheat using visible/near-infrared hyperspectral imaging and principal component analysis. *Computers and Electronics in Agriculture* **75**, 107–112.

Shahin, M.A., Symons, S.J. and Hatcher, D.W. (2014) Quantification of mildew damage in soft red winter wheat based on spectral characteristics of bulk samples: a comparison of visible-near-infrared imaging and near-infrared spectroscopy. *Food and Bioprocess Technology* **7**, 224–234.

Shao, Y., Zhao, C., He, Y. and Bao, Y. (2009) Application of infrared spectroscopy technique and chemometrics for measurement of components in rice after radiation. *Transactions of the ASABE* **52**, 187–192.

Shao, Y., Cen, Y., He, Y. and Liu, F. (2011) Infrared spectroscopy and chemometrics for the starch and protein prediction in irradiated rice. *Food Chemistry* **126**, 1856–1861.

Shatadal, P. and Tan, J. (2003) Identifying damaged soybeans by color image analysis. *Applied Engineering In Agriculture* **19**, 65–69.

Shetty, N., Min, T.-G., Gislum, R., Olesen, M. and Boelt, B. (2011) Optimal sample size for predicting viability of cabbage and radish seeds based on near infrared spectra of single seeds. *Journal of Near Infrared Spectroscopy* **19**, 451.

Shetty, N., Olesen, M.H., Gislum, R., Deleuran, L.C. and Boelt, B. (2012) Use of partial least squares discriminant analysis on visible-near infrared multispectral image data to examine germination ability and germ length in spinach seeds. *Journal of Chemometrics* **26**, 462–466.

Siemens, B.J. and Daun, J.K. (2005) Determination of the fatty acid composition of canola, flax, and solin by near-infrared spectroscopy. *Journal of the American Oil Chemists' Society* **82**, 153–157.

Singh, C.B., Jayas, D.S., Paliwal, J. and White, N.D.G. (2009a) Detection of sprouted and midge-damaged wheat kernels using near-infrared hyperspectral imaging. *Cereal Chemistry* **86**, 256–260.

Singh, C.B., Jayas, D.S., Paliwal, J., and White, N.D.G. (2009b) Detection of insect-damaged wheat kernels using near-infrared hyperspectral imaging. *Journal of Stored Products Research* **45**, 151–158.

Singh, C.B., Jayas, D.S., Paliwal, J. and White, N.G. (2010a) Identification of insect-damaged wheat kernels using short-wave near-infrared hyperspectral and digital colour imaging. *Computers and Electronics in Agriculture* **73**, 118–125.

Singh, C.B., Jayas, D.S., Paliwal, J. and White, N.D.G. (2010b) Detection of midge-damaged wheat kernels using short-wave near-infrared hyperspectral and digital colour imaging. *Biosystems Engineering* **105**, 380–387.

Singh, C.B., Jayas, D.S., Paliwal, J. and White, N.D.G. (2012) Fungal damage detection in wheat using shortwave near-infrared hyperspectral and digital colour imaging. *International Journal of Food Properties* **15**, 11–24.

Sirisomboon, C.D., Putthang, R. and Sirisomboon, P. (2013) Application of near infrared spectroscopy to detect aflatoxigenic fungal contamination in rice. *Food Control* **33**, 207–214.

Sirisomboon, P., Hashimoto, Y. and Tanaka, M. (2009) Study on non-destructive evaluation methods for defect pods for green soybean processing by near-infrared spectroscopy. *Journal of Food Engineering* **93**, 502–512.

Soto-Cámara, M., Gaitán-Jurado, A.J. and Domínguez, J. (2012) Application of near infrared spectroscopy technology for the detection of fungicide treatment on durum wheat samples. *Talanta* **97**, 298–302.

Sundaram, J., Kandala, C. V., Holser, R.A., Butts, C.L. and Windham, W.R. (2010a) Determination of in-shell peanut oil and fatty acid composition using near-infrared reflectance spectroscopy. *Journal of the American Oil Chemists' Society* **87**, 1103–1114.

Sundaram, J., Kandala, C.V.K., Butts, C.L. and Windham, W.R. (2010b) Application of NIR reflectance spectroscopy on determination of moisture content of peanuts: a non destructive analysis method. *Transactions of the ASABE* **53**, 183–189.

Sunoj, S., Igathinathane, C. and Visvanathan, R. (2016) Non-destructive determination of cocoa bean quality using FT-NIR spectroscopy. *Computers and Electronics in Agriculture* **124**, 234–242.

Tallada, J.G., Palacios-Rojas, N. and Armstrong, P.R. (2009) Prediction of maize seed attributes using a rapid single kernel near infrared instrument. *Journal of Cereal Science* **50**, 381–387.

Tallada, J.G., Wicklow, D.T., Pearson, T.C. and Armstrong, P.R. (2011) Detection of fungus-infected corn kernels using near-infrared reflectance spectroscopy and color imaging. *Transactions of the ASABE* **54**, 1151–1158.

Tigabu, M. and Odén, P.C. (2003) Discrimination of viable and empty seeds of *Pinus patula* Schiede & Deppe with near-infrared spectroscopy. *New Forestry* **25**, 163–176.

Vadivambal, R. and Jayas, D.S. (2011) Applications of thermal imaging in agriculture and food industry – a review. *Food and Bioprocess Technology* **4**, 186–199.

Vaknin, Y., Ghanim, M., Samra, S., Dvash, L., Hendelsman, E., Eisikowitch, D. and Samocha, Y. (2011) Predicting *Jatropha curcas* seed-oil content, oil composition and protein content using near-infrared spectroscopy – a quick and non-destructive method. *Industrial Crops and Products* **34**, 1029–1034.

Velasco, L. and Becker, H.C. (1998) Estimating the fatty acid composition of the oil in intact-seed rapeseed (*Brassica napus* L.) by near-infrared reflectance spectroscopy. *Euphytica* **101**, 221–230.

Velasco, L. and Möllers, C. (2002) Non-destructive assessment of protein content in single seeds of rapeseed (*Brassica napus* L.) by near-infrared reflectance spectroscopy. *Euphytica* **123**, 89–93.

Velasco, L., Möllers, C. and Becker, H.C. (1999) Estimation of seed weight, oil content and fatty acid composition in intact single seeds of rapeseed (*Brassica napus* L.) by near-infrared reflectance spectroscopy. *Euphytica* **106**, 79–85.

Venora, G., Grillo, O., Ravalli, C. and Cremonini, R. (2009) Identification of Italian landraces of bean (*Phaseolus vulgaris* L.) using an image analysis system. *Scientia Horticulturae* **121**, 410–418.

Vozáry, E., Paine, D.H., Kwiatkowski, J., and Taylor, A.G. (2007) Prediction of soybean and snap bean seed germinability by electrical impedance spectroscopy. *Seed Science & Technology* **35**, 48–64.

Wang, D., Dowell, F.E., Ram, M.S. and Schapaugh, W.T. (2004) Classification of fungal-damaged soybean seeds using near-infrared spectroscopy. *International Journal of Food Properties* **7**, 75–82.

Wang, L., Wang, Q., Liu, H., Liu, L. and Du, Y. (2012) Determining the contents of protein and amino acids in peanuts using near-infrared reflectance spectroscopy. *Journal of the Science of Food and Agriculture* **93**, 118–124.

Wang, W., Heitschmidt, G.W., Ni, X., Windham, W.R., Hawkins, S. and Chu, X. (2014) Identification of aflatoxin B1 on maize kernel surfaces using hyperspectral imaging. *Food Control* **42**, 78–86.

Weinstock, B.A., Janni, J., Hagen, L. and Wright, S. (2006) Prediction of oil and oleic acid concentrations in individual corn (*Zea mays* L.) kernels using near-infrared reflectance hyperspectral imaging and multivariate analysis. *Applied Spectroscopy* **60**, 9–16.

Williams, P., Geladi, P., Fox, G. and Manley, M. (2009) Maize kernel hardness classification by near infrared (NIR) hyperspectral imaging and multivariate data analysis. *Analytica Chimica Acta* **653**, 121–130.

Williams, P.J., Geladi, P., Britz, T.J. and Manley, M. (2012) Investigation of fungal development in maize kernels using NIR hyperspectral imaging and multivariate data analysis. *Journal of Cereal Science* **55**, 272–278.

Wilson, A.D. and Baietto, M. (2009) Applications and advances in electronic-nose technologies. *Sensors* **9**, 5099–5148.

Wittkop, B., Snowdon, R.J. and Friedt, W. (2012) New NIRS calibrations for fiber fractions reveal broad genetic variation in *Brassica napus* seed quality. *Journal of Agricultural and Food Chemistry* **60**, 2248–2256.

Wu, D. and Sun, D.-W. (2013) Advanced applications of hyperspectral imaging technology for food quality and safety analysis and assessment: a review – Part I: Fundamentals. *Innovative Food Science and Emerging Technologies* **19**, 1–14.

Wu, J. and Shi, C. (2004) Prediction of grain weight, brown rice weight and amylose content in single rice grains using near-infrared reflectance spectroscopy. *Food and Crop Research* **87**, 13–21.

Wu, Z., Zhang, J., Song, P., Li, W. and Lan, Y. (2013) A sorting method for maize haploid based on computer vision. *ASABE Annual International Meeting*, St Joseph, MI, American Society of Agricultural and Biological Engineers.

Xing, J., Van Hung, P., Symons, S., Shahin, M. and Hatcher, D. (2009) Using a short wavelength infrared (SWIR) hyperspectral imaging system to predict alpha amylase activity in individual Canadian western wheat kernels. *Sensing and Instrumentation for Food Quality and Safety* **3**, 211–218.

Xing, J., Symons, S., Shahin, M. and Hatcher, D. (2010) Detection of sprout damage in Canada Western Red Spring wheat with multiple wavebands using visible/near-infrared hyperspectral imaging. *Biosystems Engineering* **106**, 188–194.

Xing, J., Symons, S., Hatcher, D. and Shahin, M. (2011) Comparison of short-wavelength infrared (SWIR) hyperspectral imaging system with an FT-NIR spectrophotometer for predicting alpha-amylase activities in individual Canadian Western Red Spring (CWRS) wheat kernels. *Biosystems Engineering* **108**, 303–310.

Yang, X.-S., Wang, L.-L., Zhou, X.-R., Shuang, S.-M., Zhu, Z.-H., Li, N., Li, Y., Liu, F., Liu, S.-C., Lu, P. *et al.* (2013) Determination of protein, fat, starch, and amino acids in foxtail millet [*Setaria italica* (L.) Beauv.] by

Fourier transform near-infrared reflectance spectroscopy. *Food Science and Biotechnology* **22**, 1495–1500.

Yao, H., Hruska, Z., Kincaid, R., Brown, R.L., Bhatnagar, D. and Cleveland, T.E. (2013) Detecting maize inoculated with toxigenic and atoxigenic fungal strains with fluorescence hyperspectral imagery. *Biosystems Engineering* **115**, 125–135.

Yi, X., Junxiong, Z., Wei, L. and Weiguo, C. (2007) Multi-objective dynamic detection of seeds based on machine vision. *Progress in Natural Science* **17**, 217–221.

Zapotoczny, P. (2011a) Discrimination of wheat grain varieties using image analysis and neural networks. *Part I. Single kernel texture.* Journal of Cereal Science **54**, 60–68.

Zapotoczny, P. (2011b) Discrimination of wheat grain varieties using image analysis: morphological features. *European Food Research and Technology* **233**, 769–779.

Zayas, I., Lai, F.S. and Pomeranz, Y. (1986) Discrimination between wheat classes and varieties by image analysis. *Cereal Chemistry* **63**, 52–56.

Zhang, B., Rong, Z.Q., Shi, Y., Wu, J.G. and Shi, C.H. (2011) Prediction of the amino acid composition in brown rice using different sample status by near-infrared reflectance spectroscopy. *Food Chemistry* **127**, 275–281.

Zhang, X., Liu, F., He, Y. and Li, X. (2012) Application of hyperspectral imaging and chemometric calibrations for variety discrimination of maize seeds. *Sensors* **12**, 17234.

Zhou, B., Wang, J. and Qi, J. (2012) Identification of different wheat seeds by electronic nose. *International Agrophysics* **26**, 413–418.

Zhu, D., Wang, K., Zhang, D., Huang, W., Yang, G., Ma, Z. and Wang, C. (2011) Quality assessment of crop seeds by near-infrared hyperspectral imaging. *Sensor Letters* **9**, 1144–1150.

Zhu, D., Wang, C., Pang, B., Shan, F., Wu, Q. and Zhao, C. (2012) Identification of wheat cultivars based on the hyperspectral image of single seed. *Journal of Nanoelectronics and Optoelectronics* **7**, 167–172.