Trends in Food Science & Technology 56 (2016) 13–20

Contents lists available at ScienceDirect

Trends in Food Science & Technology

journal homepage: http://www.journals.elsevier.com/trends-in-food-science-and-technology

Review

Machine vision system for food grain quality evaluation: A review

P. Vithu, M.Tech., J.A. Moses, M.Tech., Ph.D. *

Indian Institute of Crop Processing Technology (IICPT), MoFPI, Govt. of India, Thanjavur, TN, 613005, India

ARTICLE INFO

Article history:
Received 4 March 2016
Accepted 22 July 2016
Available online 25 July 2016

Keywords:
Grain quality evaluation
Visual inspection
Machine vision
Image processing
Image analysis
Internal grain quality

ABSTRACT

Background: Quality of pre-processed food grains is a critical aspect and a major decider of market acceptability, storage stability, processing quality, and overall consumer acceptance. Among various indices of food grain quality evaluation, physical appearance (including external morphology) provides the foremost assessment on the condition of the grain. Conventional method of grain quality evaluation, visual inspection (a manual method) is challenging even for trained personnel in terms of rapidity, reliability and accuracy.

Scope and approach: Machine vision systems have the potential to replace manual (visual) methods of inspection and, have therefore gained wide acceptance in industries as a tool for quality evaluation of numerous agricultural products. This note provides an up-to-date review on the major applications of machine vision systems for grain quality evaluation applications in non-touching arrangement, highlighting system components, image processing and image analysis techniques, advantages and limitations of machine vision systems.

Key findings and conclusions: Machine vision systems can provide rapid and accurate information about external quality aspects of food grains. However, it is a task to integrate such systems with those that can explain internal grain quality attributes. In the near future, with ever-growing application requirements and research developments, machine vision systems can provide effective solutions for various grain quality evaluation applications.

1. Introduction

Food grains form an important part of human food and animal feed systems. World-over, 2030 million tonnes of food grains is produced annually (IGC, 2015). Quality of pre-processed food grains is a critical aspect and a major decider of market acceptability, storage stability, processing quality, and overall consumer acceptance. Grain quality decides pricing and quality indices differ based on end-use requirements. In grain handling units, quality is expressed on the basis of physical characteristics such as size, shape, kernel hardness, moisture content and visual attributes such as the presence of damaged, infested, discoloured kernels, and foreign materials. Acceptable grain quality also implies that the grain is free from adulterants and components that cause health hazards.

Conventional manual method of grain quality evaluation is challenging even for trained personnel, owing to variations in visual characteristics due to grain and environmental effects (Brosnan & Sun, 2004). Non-destructive methods of grain quality evaluation such as machine vision (Mahajan, Das, & Sardana, 2015), near infrared spectroscopy (Guindo et al. 2016), nuclear magnetic resonance spectroscopy (Horigane, Suzuki, & Yoshida, 2013), electronic nose (Lu, Deng, Zhu, & Tian, 2015), fourier transform infrared spectroscopy (Ferreira, Pallone, & Poppi, 2015), x-ray techniques (Guelpa, du Plessis, Kidd, & Manley, 2015) and hyperspectral imaging (Ravikanth, Singh, Jayas, & White, 2015) are known to overcome such limitations. This note reviews the major applications of machine vision systems for grain quality evaluation applications, highlighting system components, learning techniques, their advantages and limitation, specific to grain quality assessment. This resource will be of help to prospective researchers and grain handlers for a broader understanding on this subject.

Machine vision systems have emerged as alternate methods for inspection of visual attributes in various industries; including numerous food and agri-based applications. Their ability to provide rapid, accurate and reliable results have diversified their range of applications to bakery products (Abdullah, Aziz, & Dos-Mohamed, 2000; Davidson, Ryks, & Chu, 2001), meat and meat products (Li,

* Corresponding author.
E-mail address: moses.ja@iicpt.edu.in (J.A. Moses).

http://dx.doi.org/10.1016/j.tifs.2016.07.011
0924-2244/

Tan, & Shatadal, 2001; Tan, Morgan, Ludas, Forrest, & Gerrard, 2000), fish (Aguilera et al. 2007; Mery et al. 2011), fruits and vegetables (AL-Marakeby, Aly, & Salem, 2013; Cubero, Aleixos, Molto, Gómez-Sanchis, & Blasco, 2011; Leemans & Destain, 2004; Ogawa, Kondo, & Shibusawa, 2003) and prepared consumer foods (Pedreschi, Mery, Mendoza, & Anguiera, 2004; Wang & Sun, 2002). They are computerised and can permit cost-effective, fully automated quality evaluation systems that can replace methods of manual inspection and hence eliminate errors and inconsistencies in results. Their usage can also lower the tediousness encountered in manual inspection. Several researchers have explored the scope of utilizing machine vision systems for food grain quality inspection and classification. In this work, recent works in this field are categorized and critically discussed.

2. Machine vision systems for food grain quality evaluation

'Computer-seeing' of an object and perceiving its optical characteristics to interpret results is known as machine vision (Jha, 2010). The major components of a typical machine vision system are presented in Fig. 1. Image acquisition unit essentially consists of sample holding platform (that also acts as the imaging background), camera for capturing the image, image capture board for digitalising the image and light source for proper illumination. Digital information of the object is obtained from the acquired image and qualitative/quantitative results are provided using appropriate image processing algorithms (Gunasekaran, 2000; Sun, 2011). Image acquisition can be done using cameras (Sonka, Hlavac, & Boyle, 2008; Visen, Paliwal, Jayas, & White, 2004), or flat-bed scanners (Paliwal, Borhan, & Jayas, 2004; Shahin & Symons, 2005).

In practice, 'image acquisition' refers to the combined operation of capturing an image and using appropriate sensing devices to transfer electrical signal into a numeric form. Cameras may be colour or monochrome, with charge coupled device (CCD) or complementary metal–oxide–semiconductor sensors (CMOS); and are selected based on retrieval interphase, image format, resolution and noise-pixel ratio requirements (Brosnan & Sun, 2004; Burke, 2012; Pearson, 2009). Though cameras are preferred over scanners, flat-bed scanners can address the cost and ruggedness issues of CCD cameras (Shahin & Symons, 2001) and can also offer better consistency for image illumination (Luo, Jayas, Crowe, & Bulley, 1997; Russ, 2011). When digital cameras are used, frame grabbers can be eliminated (Zareiforoush, Minaei, Alizadeh, & Banakar, 2015), as the former digitalises images with little noise, owing to variable resolution.

Illumination is an important aspect and a cautious selection can overcome common problems such as reflection, shadowing and noises. Image clarity, repeatability and reliability of a machine vision system relies on the type of light source, power of light, method of illumination, geometry of proportion, shape of light beam and light colour (Zuech, 1988). Accordingly, the selection of components for an image acquisition system is critical as it affects pattern recognition and classification efficiency (Novini, 1995). Light sources used in machine vision systems are broadly grouped as: front lighting, back lighting, and structured lighting. Front lighting better suits applications requiring surface feature extraction while back lighting facilitates edge dimensioning and subsurface featuring applications (Soborski, 1995; Yang, 1994). It is essential that the intensity of that light source is even and controlled. Common light sources include incandescent lamps, fluorescent lamps, quartz halogen lamp, metal halide lamps, lasers, light emitting diodes (LED), X-ray tubes and infra-red lamps (Hornberg, 2007; Martin, 2007); and are selected based on application requirements.

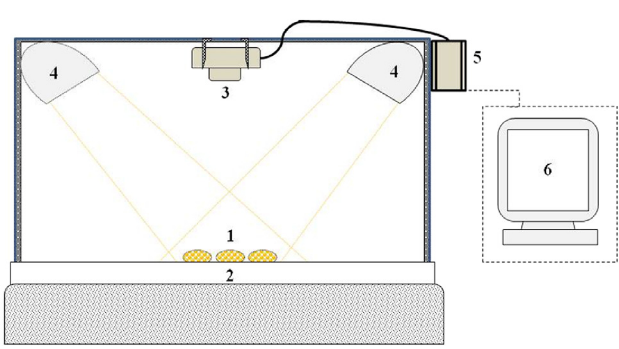

Fig. 1. Components of a Typical Machine Vision System. *1. Sample, 2. Sample holding platform (imaging background), 3. Camera, 4. Light sources, 5. Frame grabber, 6. Computer.*

The imaging background, is critical in providing appropriate contrast between object borders and background (Guevara-Hernandez & Gomez-Gil, 2011), and to eliminate object shadows (Arefi, Motlagh, & Teimourlou, 2011; Khoshroo, Arefi, Masoumiasl, & Jowkar, 2014), thus reducing complexity in image processing algorithms. Examples of imaging background colours and light sources are presented in Table 1. The choice of background colour is specific to the application.

Image processing and image analysis are the key aspects of a machine vision system (Krutz, Gibson, Cassens, & Zhang, 2000). The former aims to enhance the quality of acquired images and the latter describes processes for producing quantitative information from the image that would be used in succeeding stages for decision making. A computer being analogous to the human brain acts as the platform for processing the acquired digital image. The quality of digital image is improved prior to image analysis (termed as image pre-processing), using methods such as image resizing, image enhancement, noise removal, edge detection and filtering (Davies, 2009; Sun, 2011). An additional image segmentation operation (including threshold-based, region-based, gradient-based or classification-based method) is essential to separately identify individual grains from its background (Du & Cheng, 2014; Sun, 2000).

Recognition and interpretation are the final stages of the machine vision operation. Algorithm for most image analysis operations have been developed using proprietary software such as MATLAB or Visual C++, with specialized image processing toolboxes or other specialized packages (Rasband, 2008). Vector of features extracted from the acquired image are broadly termed 'patterns' (Jayas, Paliwal, & Visen, 2000); and the succeeding operation is to recognize these patterns based on the developed knowledge-base with extracted features from segmented images (Zareiforoush et al., 2015). Common features considered for food grain quality evaluation include: morphology, colour and texture (Table 2). In simple terms, morphology explicitly describes the geometric structure of an object, colour is an optical property and texture refers to "repeating patterns of local variations in separate objects in the image at its intensity and observed resolution" (Gonzalez & Woods, 1992).

Pattern recognition is performed using a computer learning algorithm. Most common learning techniques for grain quality evaluation using machine vision are artificial neural networks, statistical learning, fuzzy logic and genetic algorithm. Decision trees have been used for other food products (Coelho et al., 2016). Table 3 presents a short description of the underlying principle and features of each of these techniques. The objective of a learning technique is to mimic the decision making process of human vision using automated methods. Generally, all reported applications of such learning techniques are for classification and prediction; with

Table 1
Selected configurations of image acquisition systems used for food grain quality evaluation.

Sensor type	Lighting	Imaging background colour	Application	References
CCD sensor	Halogen	Blue	Identification of foreign matter	Granitto, Navone, Verdes, and Ceccatto (2002)
	Fluorescent	Black	Classification of wheat varieties	Arefi et al. (2011)
	Fluorescent	White	Classification of rice varieties	Wu, Wu, Wen, Xiong, and Zheng (2013)
	Incandescent	Maroon	Product based classification of sona-masuri rice, basmati rice, horse gram brown, horse gram white, yellow corn, gujrat wheat, orange corn and khapli wheat	Sidnal et al. (2013)
CMOS sensor	Fluorescent	Dark	Product based classification of Canada western red spring wheat, Canada western hard white wheat, Canada western amber durum wheat, barley, rye and oats	Wang and Paliwal (2006)
	LED	Silver	Identification of discoloured wheat, product based classification of barley and durum, and identification of microbial infection in wheat	Pearson (2010)
		Black	Product based classification of barley, pea and rice	Dubosclard et al. (2015)

a handful of exceptions for image segmentation and feature selection. Basically, the learning techniques work on a training set that is used to create the knowledge-base, which then acts as the reference to make decisions of any unknown case. The developed algorithm decides the classification efficiency of the entire system. Table 4 presents selected examples of artificial intelligence-based computer learning techniques used to assist image processing operations.

3. Applications in grain quality evaluation

Machine vision systems have been used in assisting grading, cleaning and separating operations in food grain handling units. In general, they have been used to identify and classify food grains based on product type, variety, refractions, and the presence of infestation/infection. A comprehensive review of these applications is presented in the following sections. Apart from these, Honda, Takikawa, Noguchi, Hanai, and Kobayashi (1997) and Duan et al. (2011) have used machine vision systems to determine root and shoot lengths and, to analyse spikelet and stalks, respectively.

3.1. Monitoring quality during processing

Machine vision system can facilitate on-line inspection of grains during processing. This can help in making changes in the process/improving efficiency and improve overall process control. An example is the study conducted by Wan, Long, and Huang (2011) to identify changes in rice colour during the milling process. Brown rice samples, samples obtained at the end of each polishing pass, and polished rice samples were studied and the effect of each processing unit operation on the physical removal of surface layers was explained. A similar concept was earlier explained by Yadav and Jindal (2001); who predicted head rice yields, indicating the scope of employing machine vision systems as a tool for rapid assessment of milling yields. They also presented relationships to explain the whiteness of milled rice; an approach that can improve quality monitoring during rice milling. Similar studies were conducted by Lloyd, Cnossen, and Siebenmorgen (2001) for both medium and long grain varieties. Earlier, Liu, Tao, Siebenmorgen, and Chen (1998) determined the area of bran layer on rice surface using digital image analysis. These researchers also correlated their results with the concentration of lipids at the kernel surface and validated their results using chemical analysis.

3.2. Grading applications

Studies have also been taken up to classify products as grades, based on variations in kernel size and shape. Kaur and Singh (2013) classified long, short, slender, bold and round grades of rice using a SVM classifier. These researchers considered variations in length (l), width (w) and l/w ratio of individual kernels as the classification criteria. The method could also differentiate head rice from brokens and brewers, based on relative differences in kernel sizes. A similar approach of classification using aspect ratio calculations was earlier used by Aggarwal and Mohan (2010). Shahin, Symons, and Poysa (2006) described the scope of using image analysis techniques for

Table 2
Typical features considered in machine vision systems for food grain quality evaluation.

Features considered	Application	Grain type	References
Morphology	Variety based classification	Rice	Rad, Tab, and Mollazade (2012)
	Identification of insect infestation	Wheat	Ridgway et al. (2002)
Colour	Identification of microbial infection	Popcorn	Yorulmaz et al. (2012)
	Identification of foreign matter	Rice	Tated and Morade (2012)
Texture	Variety based classification	Barley	Zapotoczny (2012)
	Product based classification	Canada western red spring wheat, Canada western amber durum wheat, oat and rye	Majumdar and Jayas (2000)
Colour + Texture	Variety based classification	Paddy	Anami et al. (2015)
	Product based classification	Jowar, wheat, corn, cow pea, red gram, green gram, horse gram, Bengal gram, pearl millet and peas	Patil et al. (2011)
Morphology+Colour	Product based classification	Common rice, glutinous rice, rough rice, brown rice, buckwheat, and common and glutinous barley	Lee et al. (2011)
		Canada western red spring wheat, Canada western amber durum wheat, oat and rye	Visen et al. (2004)
Morphology +Colour+Texture	Product based classification	Corn, green gram, ground nut, jowar, metagi, pea, red gram, rice, wheat and yellow gram	Anami and Savakar (2009)
		Barley and wheat	Guevara-Hernandez and Gomez-Gil (2011)

Table 3
Learning techniques in machine vision (Du & Sun, 2006; Goyal, 2013; Tellaeche, Pajares, Burgos-Artizzu, & Ribeiro, 2011 and Vapnik, 1995).

Technique	Underlying concept	Highlights[a]	Limitations[a]
Artificial neural networks	Mimics biological neurons	Higher flexibility to model systems with accurately, and ease	'Black-boxed' and tediousness in choice of topological structure
Fuzzy logic	Membership functions	Simulates human experience of making decisions based on vague information	Performance depends on how well it was tuned, making it inefficient to handle multi-dimensional problems
Genetic algorithm	Theory of natural selection and evolution	Can represent complex, multivariate conditions	Their implicit internal models are not easily understood and therefore have limited applications in this field
Statistical learning	Explicit probability model	Work on well-established underlying probability models and in several cases out-perform other learning techniques used in machine vision	Poor capability to handle non-Gaussian features
Support vector machine	Structural risk minimization	Competent to learn (with less training data) in high-dimensional feature space	Decision function considers only support vectors and not all cells relevant to a parametric function

[a] With reference to usage in machine vision systems.

visual grading of soybean considering size uniformity as the classification criteria. Further studies such as those conducted by Gunasekaran, Cooper, and Berlage (1988), Zayas, Martin, Steele, and Katsevich (1996), Luo, Jayas, and Symons (1999) and Van Dalen (2004) could identify whole and broken fractions in soybeans, corn, wheat, and rice, respectively. Additionally, Lan, Fang, Kocher, and Hanna (2002) developed a method for detection of fissures in rice kernels using machine vision and image processing. Such an approach can assist grading applications, as the presence of fissures would result in lower head rice yields during milling.

3.3. Product based classification

When multiple grain types get mixed, it is essential to segregate them prior to any further handling/processing operations. Visen et al. (2004) developed a classification methodology to differentiate wheat types, oats and rye. Colour and textural variations were considered as classification parameters. However, classification efficiencies varied for product types. Considering morphological characteristics also, Anami and Savakar (2009) could recognize several pulse and millet types. Although the applications were similar, Guevara-Hernandez and Gomez-Gil (2011) and Lee, Yan, Wang, Lee, and Park (2011) used varying imaging backgrounds (white and black, respectively) to better suit application requirements.

Automated grading systems have also been developed for grain type classification, such as those reported by Pearson (2010) and Dubosclard, Larnier, Konik, Herbulot, and Devy (2015) for the classification of barley, wheat and rice. The latter researches also considered variations in shape between grain types, for better pattern recognition. Nevertheless, inaccurate clustering algorithms would be inefficient in recognizing ellipsoidal shapes (as reported by Zhang, Jayas, & White, 2005). Alternatively, Patil, Malemath, and Yadahalli (2011) considered variations in kernel colour as the key parameter to differentiate between different pulses, based on acquired images. However, it is known that certain lentils undergo changes in seed colour owing to oxidation reactions during storage; a fact that explains why colour as the sole feature for pattern recognition would not provide accurate classification.

3.4. Variety based classification

With several new varieties available, manual differentiation of varieties is now a concern. Considering seed size measurements and colour attributes of the sample, several researchers have developed techniques to explain varietal differences in grains using

Table 4
Artificial intelligence tools used for selected machine vision applications for food grain quality evaluation.

Classifier	Application	Overall classification accuracy	References
Artificial neural networks (ANN) – back propagation	Product based classification of barley, oats, rye, wheat, and durum wheat	98%	Visen et al. (2004)
ANN-feed forward	Classification of paddy varieties (Abhilasha, Bhagyajyothi, Budda, Intan, Jaya, Jayashree, Mugad Dodiga, Mugad Sughand, Mugad 101, Mugad Siri, PSB 68, Rajakaima, Redjyothi, Thousand One and Thousand Ten)	92.33%	Anami et al. (2015)
ANN-multi-layer Perceptron	Classification of rice varieties (AT 307, BG 250, BG 358, BG 450, BW 262, BW 267, W 361 and BW 363)	92%	Silva and Sonnadara (2013)
ANN-counter Propagation	Classification of rice varieties (Ariete, Baldo, Balilla, Cripto, Drago, Elio, Lido, Loto, Selenio, Thaibonnet and Volano)	90%	Marini et al. (2004)
ANN-probabilistic	Product based classification of sona-masuri rice, basmati rice, horse gram brown, horse gram white, yellow corn, gujrat wheat, orange corn and khapli wheat	80–90%	Sidnal et al. (2013)
Fuzzy logic	Identification of rice (Pathumthani1)[a]	90%	Sansomboonsuk and Afzulpurkar (2006)
Genetic algorithm	Classification of wheat varieties (Blask, Stratus, STH 5604, STH 9731 and STH 523)	90–100%	Zapotoczny (2011)
Support vector machine	Grading applications of rice	86%	Kaur and Singh (2013)
K-nearest neighbour	Product based classification of jowar, wheat, corn, cow pea, red gram, green gram, horse gram, Bengal gram, pearl millet and peas	80–100%	Patil et al. (2011)
Bayesian classifier	Monitoring quality during processing of durum wheat	96.03%	Venora, Grillo, and Saccone (2009)

[a] Development of algorithm for separating touching kernels.

machine vision systems. Using their machine vision system, Shahin and Symons (2003) obtained classification accuracies as high as 99%; with overall process times of less than 30 s.

In an approach to classify Philippines rice varieties, Guzman and Peralta (2008) developed a machine vision-based methodology that could identify saline prone, lowland irrigated, lowland rainfed, cool elevated and upland rice varieties, considering variations in grain shape and size. Apart from these, many studies have been successfully conducted for varietal classifications of grains by extracting morphological (Dubey, Bhagwat, Shouche, & Sainis, 2006; Kiruthika, Muruganand, & Periasamy, 2013; Marini, Zupan, & Magri, 2004), colour (Golpour, Parian, & Chayjan, 2014; Shantaiya & Ansari, 2010) and textural features (Zapotoczny, 2012) and their combinations (Anami, Naveen, & Hanamaratti, 2015; Pazoki & Pazoki, 2013). Some of these are presented in Table 5.

3.5. Identification of foreign matter

Foreign matter includes organic particles such as other grain types, chaff and husk, and inorganic particles such as stones and metal pieces. Quantification of foreign material is essential as it directly affects subsequent handling, storage and processing operations. Paliwal, Visen, Jayas, and White (2003) proposed a combination of morphological, colour and textural features for dockage and foreign matter classification, based on the uniqueness of shape, size, and colour of different grains and dockage components. However, only particles with well-defined characteristics could be classified accurately, as compared to those with irregular and undefined features (such as chaff and wheat spikelets). Based on similar machine vision concepts, Tated and Morade (2012) developed a rapid automated system for cleaning impurities in rice. They proposed that the system can be effectively used in the rice milling industry.

3.6. Identification of insect infestation

Insect infestation is known to cause several quantitative and qualitative losses in food grains (Vimala, Priya, Vishnu, Moses, & Alice, 2016). During their growth stages, insect imprints may be identified using machine vision systems. For example, insect infestation (external) has been identified by inspecting holes made by insects on the kernel surface. Ebrahimi, Mollazade, and Babaei (2014) reported a classification system for identification of insect damaged wheat kernels in a bulk. Apart from the damages they cause, adult insect pests have also been identified using acquired images (Ridgway, Davies, Chambers, Mason, & Bateman, 2002).

3.7. Identification of microbial infection

Microbial infection is a serious problem in the grain industry. While under normal storage conditions bacteria do not thrive on food grains, unsafe moisture content and temperature ranges can promote the growth of fungal species such as *Aspergillus flavus*, *A. Ochraceus* and *Penicillium verrucosum* that produce toxic secondary metabolites (mycotoxins). Amongst other problems that fungal species cause is the 'Head scab' or 'Head blight' by *Fusarium* sp., resulting significant losses in crop yield; and usually accompanied with toxic deoxynivalenol (DON) production (Moses, Jayas, & Alagusundaram, 2015). Ruan et al. (1998) developed a neural network based classifier to relate color and texture features of wheat to damage caused by scab infection. Their results in terms of identification of infected kernels were more accurate than the human expert panel. Similar image analysis studies have also been conducted by Steenhoek, Misra, Hurburgh, and Bern (2001), Wiwart, Koczowska, and Borusiewicz (2001) and Jirsa and Polisenka (2014) on corn, triticale and wheat respectively.

Yet another application is the use of machine vision concepts for identification of blue-eye damages in cereals such as wheat and corn. Yorulmaz, Pearson, and Çetin (2012) developed a SVM based classification algorithm that could accurately (up to 96.5%) identify fungal damages in popcorn, based on textural variations. The method required less computational costs and hence was suggested to be used in real-time grain sorting systems.

3.8. Identification of discoloured grains

Discolouration of grains can happen under unsafe storage conditions and significantly affects market value. Difficulties in identifying discoloured and chalky kernels can be solved using machine vision systems supported by suitable classification algorithms that consider variations in colour space (Jinorose, Prachayawarakorn, & Soponronnarit, 2010). In a similar study using multivariate discriminant analysis, Ahmad, Reid, Paulsen, and Sinclair (1999) developed a Red, Green, Blue (RGB) based classification model to identify fungal/viral damages in soybean seeds (based on variations in colour features). Black germ caused by *Alternaria* sp. has also been identified in wheat, using CCD machine vision systems, with acceptable levels of accuracy. As an improved approach, Prajapati and Patel (2013) developed a mobile device for classifying Indian basmati rice into different categories. The system could also differentiate between healthy and discoloured kernels.

In another study, Azman, Bejo, Ismail, Ishak, and Wayayok (2014) proposed a methodology to study variations in kernel colour (of paddy) with maturity. Similar to other studies, this work also considered variations in RGB colour space features as the classification criteria.

4. Limitations of machine vision systems and directions for future work

In the context of quality evaluation of food grains, machine vision systems have been most commonly used to characterize grain and grain types based on visual appearance. Exceptionally, studies conducted by Yoshioka, Iwata, Tabata, Ninomiya, and Ohsawa (2007) on rice chalkiness correlated internal grain quality aspects such as starch composition, structure and cooking characteristics with acquired images (Lisle, Martin, & Fitzgerald, 2000). Similarly, Symons, Van Schepdael, and Dexter (2003) developed a methodology to identify hard vitreous kernels in durum wheat

Table 5
Examples of product-variety-based classification of different food grains using machine vision systems.

Grain type	Variety	Overall classification accuracy	References
Paddy	Kajrat-6, Ratnagiri-2, Ratnagiri-4 and Ratnagiri-24	89%	Chaugule and Mali (2014)
Rice	Khazar, Gharib, Ghasdashti, Gerdeh and Mohammadi	99%	Pazoki, Farokhi, and Pazoki (2014)
Wheat	Gohar, Dehdasht, Koohdasht and Seimareh	86%	Khoshroo et al. (2014)
Barley	Blask, Stratus, STH-5604, STH-9731 and STH-523	99%	Zapotoczny (2012)
Lentils	Laird, Richlea, Eston, Crimson and Redwing	99%	Shahin and Symons (2003)

(which could be correlated with kernel protein content). The scope of using image analysis methods to understand the physico-chemical properties of grains have also been explored (Jinorose, Prachayawarakorn, & Soponronnarit, 2014). However, most machine vision systems are not capable of understanding grain composition, internal insect infestation and organoleptic properties; factors that are critical deciders of food grain quality.

Machine vision is well-accepted as a rapid, non-destructive, non-contact and objective method of food quality evaluation (Du & Sun, 2006). However, choice, selection and calibration of system components, specific to individual application remains as the critical decider for obtaining better efficiencies. For example, poor/inconsistent lighting significantly affects acquired image quality, whilst a high quality image offers lower complexity and time for image processing. Research must be directed towards the development of real-time devices that do not get affected by operating/environmental conditions.

The other concern is the choice of the learning technique involved. Recently, researchers have considered the use of more than one type of learning technique to handle a particular operation (Sun, 2011). Combined learning techniques can outperform conventional methods, as the limitations of one technique can be addressed by another. Similarly, the use of spectral and other imaging techniques in combination with machine vision can produce better results, as reported by Huang, Zhao, Chen, and Zhang (2014) on studies conducted for other food products. This is because the spectral ranges of infrared, near infrared, ultraviolet and X-ray sources can provide critical data, otherwise not obtained through visible light sources only (Heia et al. 2007; Yang, Chao, & Chen, 2005).

In general, machines working on image acquisition and processing methods require skilled labour and suffer problems with tedious trouble-shooting procedures. While computer oriented algorithms can be quickly developed, tested and debugged, their usage in real-time systems is often restricted owing to increased computational requirements. This may be overcome with hardware replacements such as a digital signal processor; with associated escalating costs. Another aspect relevant to system costs is the choice of the image acquisition system. Flat-bed scanners, such as the one used by Paliwal et al. (2004) can lower system costs, but their usage may not be suitable for most real-time applications. However, it is also argued that high performances obtained using machine vision systems out-weigh system costs (Narendra & Hareesha, 2010).

Considering more number of grain features can provide accurate classifications; at the cost of increased computation and poor consistencies (Sidnal, Patil, & Patil, 2013). Also, most developed systems for grain quality applications work on algorithms developed to identify and classify non-touching kernels; a case which is not very practical for on-line applications in the grain handling industry. It continues to remain a challenge for handling cases involving overlapping objects and for those where images of multiple sides of a grain must be considered (Brosnan & Sun, 2004). Addressing such issues will eliminate false positives and poor classification accuracies.

5. Conclusion

Machine vision systems are non-destructive, non-contact and non-invasive methods of food grain quality evaluation. The approach can provide rapid and accurate information about external quality aspects of food grains. They can be used for identification and classification of grain types and varieties, foreign matter, insect infestation, microbial infection, and grain discolouration. It is also possible to monitor grain quality during various stages of grain processing, and to employ machine vision systems for grain grading applications. The major challenge however, it to integrate such systems with those that can explain internal grain quality attributes. In the near future, with ever-growing application requirements and research developments, machine vision systems can provide effective solutions for various grain quality evaluation applications.

References

Abdullah, Z. M., Aziz, A. S., & Dos-Mohamed, A. M. (2000). Quality inspection of bakery products using a colour-based machine vision system. *Journal of Food Quality, 23*(1), 39–50.

Aggarwal, A. K., & Mohan, R. (2010). Aspect ratio analysis using image processing for rice grain quality. *International Journal of Food Engineering, 6*(5).

Aguilera, J., Cipriano, A., Erana, M., Lillo, I., Mery, D., & Soto, A. (2007). Computer vision for quality control in Latin American food industry, a case study. In *International conference on computer vision: Workshop on computer vision applications for developing countries (ICCV2007)* (pp. 1–8).

Ahmad, I. S., Reid, J. F., Paulsen, M. R., & Sinclair, J. B. (1999). Color classifier for symptomatic soybean seeds using image processing. *Plant Disease, 83*, 320–327.

AL-Marakeby, A., Aly, A. A., & Salem, F. A. (2013). Fast quality inspection of food products using computer vision. *Advanced Research in Computer and Communication Engineering, 2*(11), 4168–4171.

Anami, B. S., Naveen, N. M., & Hanamaratti, N. G. (2015). Behavior of HSI color co-occurrence features in variety recognition from bulk paddy grain image samples. *International Journal of Signal Processing, Image Processing & Pattern Recognition, 8*(4).

Anami, B. S., & Savakar, D. (2009). Effect of foreign bodies on recognition and classification of bulk food grains image samples. *Journal of Applied Computer Science, 6*(3), 77–83.

Arefi, A., Motlagh, A. M., & Teimourlou, R. F. (2011). Wheat class identification using computer vision system and artificial neural networks. *International Agrophysics, 25*(4).

Azman, N., Bejo, S. K., Ismail, W., Ishak, W., & Wayayok, A. (2014). Estimating maturity of paddy using RGB colour space. *Journal of Advanced Agricultural Technologies, 1*(2), 119–124.

Brosnan, T., & Sun, D. W. (2004). Improving quality inspection of food products by computer vision – A review. *Journal of Food Engineering, 61*, 3–16.

Burke, M. W. (2012). *Image acquisition: Handbook of machine vision engineering* (vol. 1). London, UK: Chapman and Hall.

Chaugule, A., & Mali, S. N. (2014). Evaluation of texture and shape features for classification of four paddy varieties. *Journal of Engineering*, 1–8.

Coelho, P. A., Torres, S. N., Ramírez, W. E., Gutiérrez, P. A., Toro, C. A., Soto, J. G., et al. (2016). A machine vision system for automatic detection of parasites Edotea magellanica in shell-off cooked clam Mulinia edulis. *Journal of Food Engineering, 181*, 84–91.

Cubero, S., Aleixos, N., Molto, E., Gómez-Sanchis, J., & Blasco, J. (2011). Advances in machine vision applications for automatic inspection and quality evaluation of fruits and vegetables. *Food and Bioprocess Technology, 4*(4), 487–504.

Davidson, V. J., Ryks, J., & Chu, T. (2001). Fuzzy models to predict consumer ratings for biscuits based on digital image features. *IEEE Transactions on Fuzzy Systems, 9*(1), 62–67.

Davies, E. R. (2009). The application of machine vision to food and agriculture: A review. *The Imaging Science Journal, 57*(4), 197–217.

Duan, L., Yang, W., Bi, K., Chen, S., Luo, Q., & Liu, Q. (2011). Fast discrimination and counting of filled/unfilled rice spikelets based on bi-modal imaging. *Computers and Electronics in Agriculture, 75*(1), 196–203.

Dubey, B. P., Bhagwat, S. G., Shouche, S. P., & Sainis, J. K. (2006). Potential of artificial neural networks in varietal identification using morphometry of wheat grains. *Biosystems Engineering, 95*(1), 61–67.

Dubosclard, P., Larnier, S., Konik, H., Herbulot, A., & Devy, M. (2015). Automated visual grading of grain kernels by machine vision. In *ISOP: Proceedings of 12th international conference on quality control by artificial vision, Le Creusot, France, April 2015*.

Du, C. J., & Cheng, Q. (2014). Kernel fuzzy c-means, K. F. C. M. In *Process analytical technology for the food industry* (vol. 157).

Du, C. J., & Sun, D. W. (2006). Learning techniques used in computer vision for food quality evaluation: A review. *Journal of Food Engineering, 72*(1), 39–55.

Ebrahimi, E., Mollazade, K., & Babaei, S. (2014). Toward an automatic wheat purity measuring device: A machine vision-based neural networks-assisted imperialist competitive algorithm approach. *Measurement, 55*, 196–205.

Ferreira, D. S., Pallone, J. A. L., & Poppi, R. J. (2015). Direct analysis of the main chemical constituents in Chenopodium quinoa grain using Fourier transform near-infrared spectroscopy. *Food Control, 48*, 91–95.

Golpour, I., Parian, J. A., & Chayjan, R. A. (2014). Identification and classification of bulk paddy, brown, and white rice cultivars with colour features extraction using image analysis and neural network. *Czech Journal of Food Sciences, 32*(3), 280–287.

Gonzalez, R. C., & Woods, R. E. (1992). *Digital imaging processing*. Massachusetts: Addison-Wesley.

Goyal, S. (2013). Predicting properties of cereals using artificial neural networks: A

review. *Scientific Journal of Crop Science, 2*(7), 95–115.
Granitto, P. M., Navone, H. D., Verdes, P. F., & Ceccatto, H. A. (2002). Weed seeds identification by machine vision. *Computers and Electronics in Agriculture, 33*(2), 91–103.
Guelpa, A., du Plessis, A., Kidd, M., & Manley, M. (2015). Non-destructive estimation of maize (Zea mays L.) kernel hardness by means of an X-ray micro-computed tomography (μCT) density calibration. *Food and Bioprocess Technology, 8*, 1419–1429.
Guevara-Hernandez, F., & Gomez-Gil, J. (2011). A machine vision system for classification of wheat and barley grain kernels. *Spanish Journal of Agricultural Research, 9*(3), 672–680.
Guindo, D., Davrieux, F., Teme, N., Vaksmann, M., Doumbia, M., Fliedel, G., et al. (2016). Pericarp thickness of sorghum whole grain is accurately predicted by NIRS and can affect the prediction of other grain quality parameters. *Journal of Cereal Science, 69*, 218–227.
Gunasekaran, S. (2000). *Nondestructive food evaluation: techniques to analyze properties and quality*. Madison, Wisconsin: CRC Press.
Gunasekaran, S., Cooper, T. M., & Berlage, A. G. (1988). Soybean seed coat and cotyledon crack detection by image processing. *Journal of Agricultural Engineering Research, 41*(2), 139–148.
Guzman, J. D., & Peralta, E. K. (2008). Classification of Philippine rice grains using machine vision and artificial neural networks. In *World conference on agricultural information and IT, Tokyo, Japan, August 2008* (pp. 24–27).
Heia, K., Sivertsen, A. H., Stormo, S. K., Elvevoll, E., Wold, J. P., & Nilsen, H. (2007). Detection of nematodes in cod (*Gadus morhua*) fillets by imaging spectroscopy. *Journal of Food Science, 72*(1), 11–15.
Honda, H., Takikawa, N., Noguchi, H., Hanai, T., & Kobayashi, T. (1997). Image analysis associated with a fuzzy neural network and estimation of shoot length of regenerated rice callus. *Journal of Fermentation and Bioengineering, 84*, 342–347.
Horigane, A. K., Suzuki, K., & Yoshida, M. (2013). Moisture distribution of soaked rice grains observed by magnetic resonance imaging and physicochemical properties of cooked rice grains. *Journal of Cereal Science, 57*(1), 47–55.
Hornberg, A. (2007). *Handbook of machine vision*. Germany: John Wiley & Sons.
Huang, L., Zhao, J., Chen, Q., & Zhang, Y. (2014). Nondestructive measurement of total volatile basic nitrogen (TVB-N) in pork meat by integrating near infrared spectroscopy, computer vision and electronic nose techniques. *Food Chemistry, 145*, 228–236.
International Grain Council. (2015). *Global market report*. Available at: http://www.igc.int/downloads/gmrsummary/gmrsumme.pdf Accessed on 08.12.15.
Jayas, D. S., Paliwal, J., & Visen, N. S. (2000). Review paper (AE—Automation and emerging technologies): Multi-layer neural networks for image analysis of agricultural products. *Journal of Agricultural Engineering Research, 77*(2), 119–128.
Jha, S. N. (2010). *Nondestructive evaluation of food quality*. Heidelberg: Springer.
Jinorose, M., Prachayawarakorn, S., & Soponronnarit, S. (2010). Development of a computer vision system and novel evaluation criteria to characterize color and appearance of rice. *Drying Technology, 28*(9), 1118–1124.
Jinorose, M., Prachayawarakorn, S., & Soponronnarit, S. (2014). A novel image-analysis based approach to evaluate some physicochemical and cooking properties of rice kernels. *Journal of Food Engineering, 124*, 184–190.
Jirsa, O., & Polisenka, I. (2014). Identification of Fusarium damaged wheat kernels using image analysis. *Acta Universitatis Agriculturae Et Silviculturae Mendelianae Brunensis, 59*(5), 125–130.
Kaur, H., & Singh, B. (2013). Classification and grading rice using multi-class SVM. *International Journal of Scientific and Research Publications, 3*(4), 1–5.
Khoshroo, A., Arefi, A., Masoumiasl, A., & Jowkar, G. H. (2014). Classification of wheat cultivars using image processing and artificial neural networks. *Agricultural Communications, 2*(1), 17–22.
Kiruthika, R., Muruganand, S., & Periasamy, A. (2013). Matching of different rice grains using digital image processing. *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, 2*(7), 2937–2941.
Krutz, G. W., Gibson, H. G., Cassens, D. L., & Zhang, M. (2000). Colour vision in forest and wood engineering. *Landwards, 55*, 2–9.
Lan, Y., Fang, Q., Kocher, M. F., & Hanna, M. A. (2002). Detection of fissures in rice grains using imaging enhancement. *International Journal of Food Properties, 5*(1), 205–215.
Leemans, V., & Destain, M. F. (2004). A real-time grading method of apples based on features extracted from defects. *Journal of Food Engineering, 61*(1), 83–89.
Lee, C. Y., Yan, L., Wang, T., Lee, S. R., & Park, C. W. (2011). Intelligent classification methods of grain kernels using computer vision analysis. *Measurement Science and Technology, 22*(6), 64006.
Lisle, A. J., Martin, M., & Fitzgerald, M. A. (2000). Chalky and translucent rice grains differ in starch composition and structure and cooking properties. *Cereal Chemistry, 77*(5), 627–632.
Li, J., Tan, J., & Shatadal, P. (2001). Classification of tough and tender beef by image texture analysis. *Meat Science, 57*(4), 341–346.
Liu, W., Tao, Y., Siebenmorgen, T. J., & Chen, H. (1998). Digital image analysis method for rapid measurement of rice degree of milling. *Cereal chemistry, 75*(3), 380–385.
Lloyd, B. J., Cnossen, A. G., & Siebenmorgen, T. J. (2001). Evaluation of two methods for separating head rice from brokens for head rice determination. *Applied Engineering in Agriculture, 17*(5), 643.
Lu, L., Deng, S., Zhu, Z., & Tian, S. (2015). Classification of rice by combining electronic tongue and nose. *Food Analytical Methods, 8*(8), 1893–1902.
Luo, X., Jayas, D. S., Crowe, T. G., & Bulley, N. R. (1997). Evaluation of light sources for machine vision. *Canadian Agricultural Engineering, 39*, 309–315.
Luo, X. Y., Jayas, D. S., & Symons, S. J. (1999). Identification of damaged kernels in wheat using a colour machine vision system. *Journal of Cereal Science, 30*, 49–59.
Mahajan, S., Das, A., & Sardana, H. K. (2015). Image acquisition techniques for assessment of legume quality. *Trends in Food Science & Technology, 42*(2), 116–133.
Majumdar, S., & Jayas, D. S. (2000). Classification of cereal grains using machine vision III: Texture models. *Transactions of American Society of Agricultural Engineers, 43*, 1681–1687.
Marini, F., Zupan, J., & Magri, A. L. (2004). On the use of counter propagation artificial neural networks to characterize Italian rice varieties. *Analytica Chimica Acta, 510*, 231–240.
Martin, D. (2007). *A practical guide to machine vision lighting* (Midwest Sales and Support Manager, Advanced illumination).
Mery, D., Lillo, I., Loebel, H., Riffo, V., Soto, A., Cipriano, A., et al. (2011). Automated fish bone detection using X-ray imaging. *Journal of Food Engineering, 105*(2011), 485–492.
Moses, J. A., Jayas, D. S., & Alagusundaram, K. (2015). Climate change and its implications on stored food grains. *Agricultural Research, 4*(1), 21–30.
Narendra, V. G., & Hareesha, K. S. (2010). Prospects of computer vision automated grading and sorting systems in agricultural and food products for quality evaluation. *International Journal of Computer Applications, 1*(4), 1–9.
Novini, A. (1995). The latest in vision technology in today's food and beverage container manufacturing industry. In *Food processing automation IV Proceedings of the conference*. Michigan, USA: St. Joseph.
Ogawa, Y., Kondo, N., & Shibusawa, S. (2003). Inside quality evaluation of fruit by X-ray image. In *Proceedings of international conference on advanced intelligent mechatronics* (vol. 2, pp. 1360–1365).
Paliwal, J., Borhan, M. S., & Jayas, D. S. (2004). Classification of cereal grains using a flatbed scanner. *Canadian Biosystems Engineering, 46*, 3–1.
Paliwal, J., Visen, N. S., Jayas, D. S., & White, N. D. G. (2003). Cereal grain and dockage identification using machine vision. *Biosystems Engineering, 85*(1), 51–57.
Patil, N. K., Malemath, V. S., & Yadahalli, R. M. (2011). Color and texture based identification and classification of food grains using different color models and haralick features. *International Journal on Computer Science and Engineering, 3*(12), 3669.
Pazoki, A. R., Farokhi, F., & Pazoki, Z. (2014). Classification of rice grain varieties using two artificial neural networks (MLP and Neuro-Fuzzy). *Journal of Animal and Plant Sciences, 24*, 336–343.
Pazoki, A., & Pazoki, Z. (2013). Classification system for rain fed wheat grain cultivars using artificial neural network. *African Journal of Biotechnology, 10*(41), 8031–8038.
Pearson, T. (2009). Hardware-based image processing for high-speed inspection of grains. *Computers and Electronics in Agriculture, 69*(1), 12–18.
Pearson, T. (2010). High-speed sorting of grains by color and surface texture. *Applied Engineering in Agriculture, 26*(3), 499–505.
Pedreschi, F., Mery, D., Mendoza, F., & Anguiera, J. M. (2004). Classification of potato chips using pattern recognition. *Journal of Food Science, 69*, 264–270.
Prajapati, B. B., & Patel, S. (2013). Proposed mobile rice grain analyzer device based on digital image processing with related hardware and software specifications. *American International Journal of Research in Science, Technology, Engineering and Mathematics, 13*, 217–220.
Rad, S. M., Tab, F. A., & Mollazade, K. (2012). Application of imperialist competitive algorithm for feature selection: A case study on bulk rice classification. *International Journal of Computer Applications, 40*(16), 41–47.
Rasband, W. S. (2008). *Image J*. Bethesda, Maryland, USA: US National Institutes of Health. Available from http://rsb.info.nih.gov/ij/index.html Accessed on 28.12.2015.
Ravikanth, L., Singh, C. B., Jayas, D. S., & White, N. D. (2015). Classification of contaminants from wheat using near-infrared hyperspectral imaging. *Biosystems Engineering, 135*, 73–86.
Ridgway, C., Davies, E. R., Chambers, J., Mason, D. R., & Bateman, M. (2002). Rapid machine vision method for the detection of insects and other particulate bio-contaminants of bulk grain in transit. *Biosystems Engineering, 83*, 21–30.
Ruan, R., Ning, S., Song, A., Ning, A., Jones, R., & Chen, P. (1998). Estimation of fusarium scab in wheat using machine vision and a neural network. *Cereal chemistry, 75*(4), 455–459.
Russ, J. C. (2011). *The image processing handbook*. Raleigh, North Carolina, US: CRC Press.
Sansomboonsuk, S., & Afzulpurkar, N. (2006). The appropriate algorithms of image analysis for rice kernel quality evalution. In *20th conference of mechanical engineering network of Thailand, October 2006, Bangkok, Thailand* (pp. 18–20).
Shahin, M. A., & Symons, S. J. (2001). A machine vision system for grading lentils. *Canadian Biosystems Engineering, 43*, 7.
Shahin, M. A., & Symons, S. J. (2003). Lentil type identification using machine vision. *Canadian Biosystems Engineering, 45*, 3–5.
Shahin, M. A., & Symons, S. J. (2005). Seed sizing from images of non-singulated grain samples. *Canadian Biosystems Engineering, 47*(3), 49–55.
Shahin, M. A., Symons, S. J., & Poysa, V. W. (2006). Determining soya bean seed size uniformity with image analysis. *Biosystems Engineering, 94*(2), 191–198.
Shantaiya, S., & Ansari, U. (2010). Identification of food grains and its quality using pattern classification. In *12th IEEE international conference on communication technology (ICCT), November 2010, Nanjing, China* (pp. 11–14).

Sidnal, N., Patil, V. U., & Patil, P. (2013). Grading and quality testing of food grains using neural network. *International Journal of Research in Engineering and Technology, 2*(11).

Silva, C. S., & Sonnadara, U. (2013). Classification of rice grains using neural networks. *Proceedings of Technical Sessions, 29*, 9–14.

Soborski, M. L. (1995). Machine vision inspection for improved quality and production in the food processing environment. In *Food processing automation IV Proceedings of the FPAC conference*. Michigan, USA: St. Joseph.

Sonka, M., Hlavac, V., & Boyle, R. (2008). *Image processing, analysis, and machine vision*. Stamford, USA: Cengage Learning.

Steenhoek, L. W., Misra, M. K., Hurburgh, C. R., Jr., & Bern, C. J. (2001). Implementing a computer vision system for corn kernel damage evaluation. *Applied Engineering in Agriculture, 17*(23), 235.

Sun, D. W. (2000). Inspecting pizza topping percentage and distribution by a computer vision method. *Journal of Food Engineering, 44*(4), 245–249.

Sun, D. W. (2011). *Computer vision technology for food quality evaluation*. Dublin, Ireland: Academic Press.

Symons, S. J., Van Schepdael, L., & Dexter, J. E. (2003). Measurement of hard vitreous kernels in durum wheat by machine vision 1. *Cereal Chemistry, 80*(5), 511–517.

Tan, F. J., Morgan, M. T., Ludas, L. I., Forrest, J. C., & Gerrard, D. C. (2000). Assessment of fresh pork colour with colour machine vision. *Journal of Animal Science, 78*(12), 3078–3085.

Tated, K., & Morade, S. (2012). Application of image processing for automatic cleaning of rice. In *Proceedings of the 1st international conference on recent trends in engineering & technology, March 2012, Nashik, India* (pp. 215–217).

Tellaeche, A., Pajares, G., Burgos-Artizzu, X. P., & Ribeiro, A. (2011). A computer vision approach for weeds identification through Support Vector Machines. *Applied Soft Computing, 11*(1), 908–915.

Van Dalen, G. (2004). Determination of the size distribution and percentage of broken kernels of rice using flatbed scanning and image analysis. *Food Research International, 37*(1), 51–58.

Vapnik, V. (1995). *The nature of statistical learning theory*. New York, USA: Springer Verlag.

Venora, G., Grillo, O., & Saccone, R. (2009). Quality assessment of durum wheat storage centres in sicily: Evaluation of vitreous, starchy and shrunken kernels using an image analysis system. *Journal of Cereal Science, 49*(3), 429–440.

Vimala, B. S. K., Priya, V. V., Vishnu, E., Moses, J. A., & Alice, R. P. S. (2016). *Insect infestation and losses in stored food grains* (Accepted for publication in Ecology, Environment and Conservation).

Visen, N. S., Paliwal, J., Jayas, D. S., & White, N. D. G. (2004). Image analysis of bulk grain samples using neural networks. *Canadian Agricultural Engineering, 46*, 7.11–7.15.

Wang, W., & Paliwal, J. (2006). Separation and identification of touching kernels and dockage components in digital images. *Canadian Biosystems Engineering, 48*, 7.

Wang, H. H., & Sun, D. W. (2002). Melting characteristics of cheese: Analysis of effects of cooking conditions using computer vision techniques. *Journal of Food Engineering, 52*(3), 279–284.

Wan, P., Long, C., & Huang, X. (2011). A detection method of rice process quality based on the color and BP Neural Network. *Computer and Computing Technologies in Agriculture, IV*, 25–34.

Wiwart, M., Koczowska, I., & Borusiewicz, A. (2001). Estimation of Fusarium head blight of triticale using digital image analysis of grain. *Computer analysis of images and patterns* (pp. 563–569).

Wu, L. L., Wu, J., Wen, Y. X., Xiong, L. R., & Zheng, Y. (2013). Classification of single cereal grain kernel using shape parameters based on machine vision. *Advanced Materials Research, 605*, 2179–2182.

Yadav, B. K., & Jindal, V. K. (2001). Monitoring milling quality of rice by image analysis. *Computers and Electronics in Agriculture, 33*(1), 19–33.

Yang, Q. (1994). An approach to apple surface feature detection by machine vision. *Computers and Electronics in Agriculture, 11*, 249–264.

Yang, C.-C., Chao, K., & Chen, Y.-R. (2005). Development of multispectral image processing algorithms for identification of wholesome, septicemic, and inflammatory process chickens. *Journal of Food Engineering, 69*, 225–234.

Yorulmaz, O., Pearson, T. C., & Çetin, A. E. (2012). Detection of fungal damaged popcorn using image property covariance features. *Computers and Electronics in Agriculture, 84*, 47–52.

Yoshioka, Y., Iwata, H., Tabata, M., Ninomiya, S., & Ohsawa, R. (2007). Chalkiness in rice: Potential for evaluation with image analysis. *Crop Science, 47*(5), 2113–2120.

Zapotoczny, P. (2011). Discrimination of wheat grain varieties using image analysis and neural networks. Part I. Single kernel texture. *Journal of Cereal Science, 54*(1), 60–68.

Zapotoczny, P. (2012). Application of image texture analysis for varietal classification of barley. *International Agrophysics, 26*(1), 81–90.

Zareiforoush, H., Minaei, S., Alizadeh, M. R., & Banakar, A. (2015). Qualitative classification of milled rice grains using computer vision and metaheuristic techniques. *Journal of Food Science and Technology*, 1–14.

Zayas, I. Y., Martin, C. R., Steele, J. L., & Katsevich, A. (1996). Wheat classification using image analysis and crush-force parameters. *Transactions of the American Society of Agricultural Engineers, 39*(6), 2199–2204.

Zhang, G., Jayas, D. S., & White, N. D. G. (2005). Separation of touching grain kernels in an image by ellipse fitting algorithm. *Biosystems Engineering, 92*, 135–142.

Zuech, N. (1988). *Applying machine vision*. New York, USA: John Wiley & Sons, Inc.