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Review

Machine vision system for food grain quality evaluation: A review

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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,

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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.

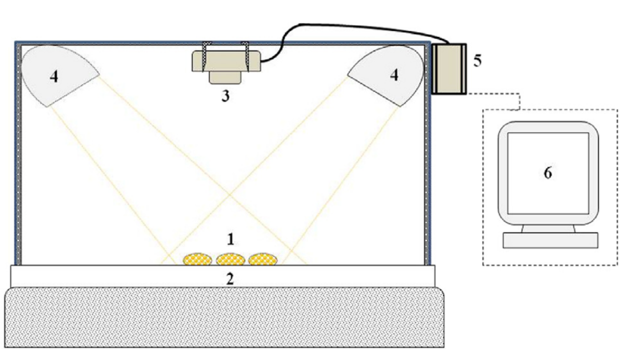

Fig. 1. Components of a Typical Machine Vision System. *1. Sample, 2. Sample holding platform (imaging background), 3. Camera, 4. Light sources, 5. Frame grabber, 6. Computer.*

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