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Classification of white maize defects with multispectral imaging

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ABSTRACT

Multispectral imaging with object-wise multivariate image analysis was evaluated for its potential to grade whole white maize kernels. The types of defective materials regarded in grading legislation were divided into 13 classes, and were imaged with a multispectral imaging instrument spanning the UV, visible and NIR regions (19 wavelengths ranging from 375 to 970 nm). Object-wise partial least squares discriminant analysis (PLS-DA) models were developed and validated with an independent data set. Results demonstrated good performance in distinguishing between sound maize and undesirable materials, with cross-validated coefficients of determination (Q^2) and classification accuracies ranging from 0.35 to 0.99 and 83 to 100%, respectively. Wavelengths related to absorbance of green, yellow and orange colour indicated the presence of lycopene and anthocyanin (505, 525, 570 and 590 nm). NIR wavelengths 890, 940 nm (associated with fat) and 970 nm (associated with water) were generally identified as important features throughout the study.

1. Introduction

Maize (*Zea mays* L.) is a widely consumed and grown cereal crop. It can be found in many forms such as minimally processed staple foods (porridges and breads), processed foods (tortillas, chips and breakfast cereals), and alcohol production (Fox & Manley, 2009). Generally, developing regions such as Africa, South America and Asia consume maize directly as staple food (Fox & Manley, 2009). In developed countries, maize is more often consumed as second-cycle produce, in the form of meat, eggs and dairy (Scanes, 2010). Maize, particularly white maize, is a vital food source for African people, including the majority of the South African population (Gouse, Pray, Schimmelpfennig, & Kirsten, 2006). In South Africa, white maize is typically consumed as a minimally processed unfermented porridge, which is commonly the basis of most meals.

Grading is an important step that evaluates whole maize kernels' suitability for human consumption. The main aim of grading is to determine the condition and health of the grain. Regardless of the specific end product being produced, certain grading quality and safety characteristics are important for all human food uses (Eckhoff & Paulsen, 2012). The grading of maize also facilitates fair trading between buyers and sellers by providing an indication of its intrinsic value. In South Africa, a very simple manual grading method is followed where a sample (150 g minimum) is visually inspected to identify any content other than sound white maize, such as defective grain or foreign material (Department of Agriculture, 2009). Undesirable materials, within each defective category, are weighed and referenced to stipulated maximum levels. This method is extremely labour intensive and can be considered subjective. Spectral imaging has been identified as a more objective alternative to potentially replace visual inspection.

Multispectral imaging is a form of spectral imaging in which a relatively small number of wavelengths is used, e.g. 10 instead of 250 (Gowen, O'Donnell, Cullen, Downey, & Frias, 2007). As with hyperspectral imaging, which is more commonly used in food science and technology, it is a non-destructive technique that combines spectroscopy and computer imaging, enabling chemical and spatial information to be acquired simultaneously (Ariana, Guyer, & Shrestha, 2006; Dissing, Clemmesen, Løje, Ersbøll, & Adler-Nissen, 2009). However, by utilising only a small number of key wavelengths rather than a continuous range, multispectral imaging instruments are simple, rapid and relatively inexpensive. The current scan time of about 10 s for hyperspectral instruments is too slow for some online industry applications (Yan et al., 2017). Since multispectral imaging is based on far fewer spectral wavelengths, faster image acquisition of about 2 s is possible. Furthermore, the inclusion of only a few discrete wavelengths enables multispectral instruments to be manufactured at lower costs. If multispectral imaging can prove capable of similar applications as hyperspectral imaging at suitable accuracies, its higher throughput and lower cost is favourable for industry applications.

Multispectral systems show great promise for on-line cereal grading and evaluation (Liu, Liu, Lu, Chen et al., 2014). Although multispectral imaging has been less widely utilised, successful food applications include the evaluation of red meat (Liu, Cao, et al., 2016; Ropodi, Panagou, & Nychas, 2013; Ropodi, Pavlidis, Mohareb,

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Panagou, & Nychas, 2015; Trinderup, Dahl, Jensen, Carstensen, & Conradsen, 2013), fish (Ljungqvist et al., 2012), prepared meal components (Dissing et al., 2009), fruits and vegetables (Ariana et al., 2006; Liu, Liu, Lu, Ma, et al., 2014; Shrestha, Deleuran, Olesen, & Gislum, 2015), cereals (Bodevin et al., 2009; Liu, Liu, Lu, Chen et al., 2014; Liu, Liu, et al., 2016), and baked cereal products (Andresen, Dissing, & Løje, 2013). Due to the ability to predict multiple components simultaneously, an on-line multispectral imaging system has the potential to replace multiple conventional chemical, microbial or physical tests with a single, automated image acquisition (Dissing et al., 2009).

Many applications of spectral imaging in cereal research utilise the near infrared (NIR) region. However, the visible or ultraviolet (UV) regions have been used (Berman et al., 2007; Del Fiore et al., 2010; Wang, Sun, Pu, & Zhu, 2015). The use of these regions is fitting, as the undesirable materials given in the South African maize grading legislation are all identifiable using human visual inspection. While chemical differences may be used to differentiate classes, as is done in NIR hyperspectral imaging, both visible and chemical differences between the samples will be apparent to an instrument operating in the visible region. An advantage of using visible wavelengths instead of those in the NIR region is a reduction in cost of the camera. This cost is further reduced when fewer wavebands are used, as one moves from hyperspectral to multispectral imaging. A powerful NIR hyperspectral instrument with 250 wavebands would cost about ten times as much as a simple multispectral camera built for a specific purpose and utilising 3 or 4 carefully chosen NIR or visible wavebands.

Although using fewer wavelengths than hyperspectral imaging, multispectral imaging still generates large datasets, requiring image analysis to gain meaningful insight from the data (Esbensen & Geladi, 1989; Manley, 2014). While traditional multivariate image analysis methods analyse all pixels in an image individually, some applications are better suited for an object-wise approach (Kucheryavskiy, 2013). The average spectrum of all pixels in an object, such as a kernel, is used during modelling. This is appropriate when emulating manual grading, as whole maize kernels must be observed as the lowest unit of measurement. This method has proved more effective in cases where objects from different classes have many similar pixels (Kucheryavskiy, 2013; Williams & Kucheryavskiy, 2016).

The aim of this study was to evaluate the capability of multispectral imaging paired with an object-wise approach to PLS-DA classification to separate sound white maize kernels from defective kernels and undesirable materials of different categories typically encountered in South African maize.

2. Materials and methods

2.1. Samples

Maize kernels and undesirable materials were obtained from the Southern African Grain Laboratory (SAGL, Pretoria, South Africa) and were graded visually by expert graders according to South African grading regulations (Department of Agriculture, 2009). Of the 19 defects stipulated in the grading regulation, 13 were evaluated during this study since these were prevalent during the 2015 season. The graders provided all defected kernels, which resulted in at least 18 kernels per defect, to be included in the sample set. Subsequently, 910 maize kernels were used in total (13 two-way analyses of 35 kernels, including unique calibration and validation kernels). This number of kernels are typical for hyperspectral imaging studies of cereals (Del Fiore et al., 2010; McGoverin, Engelbrecht, Geladi, & Manley, 2011; Tekle, Måge, Segtnan, & Bjørnstad, 2015; Williams & Kucheryavskiy, 2016). These 13 most prolific undesirable materials were distinguished from the sound maize class. Classes included defective white maize (heat damage, water damage, screenings/broken kernels, *Fusarium* fungal damage and *Diplodia* fungal damage); pinked white maize; other colour maize (i.e. yellow maize); and foreign matter (wheat, soy, sunflower seeds, sorghum and maize plant material).

2.2. Multispectral imaging system

Multispectral images were acquired with a VideometerLab2 (Videometer, Hørsholm, Denmark) multispectral imaging system. The samples were placed beneath an integrating or Ulbricht sphere, with a camera located in the top of the sphere. During image capture, the sphere closes over the sample stage to create optically closed conditions, allowing even lighting with minimal shadows and specular reflection. Samples were illuminated by 19 high power light emitting diodes (LEDs) that were evenly spaced along the equator of the sphere. A spectral range of 375 to 970 nm was utilised, at specific wavelengths: 375; 405; 435; 450; 470; 505; 525; 570; 590; 630; 645; 660; 700; 780; 850; 870; 890; 940; and 970 nm. The LEDs strobe successively in a scan time of *ca.* 5 s, resulting in an image for each LED. The images consisted of 2056 × 2056 pixels, with a high spatial resolution of approximately 45 μm/pixel. Instrument calibration was performed approximately once an hour using two reflectance targets (25 and 75% reflectance) and one geometric target to obtain the optimal dynamic range for each LED and minimize lens distortions.

2.3. Image acquisition

For the calibration set, a pair of images (germ-up and -down) of each of the 13 undesirable material classes with the sound maize kernels were captured. These data sets consisted of 17 sound maize kernels (top 3–4 rows in the image) and 18 undesirable material kernels/objects of a single class (bottom 3–4 rows in the image), giving a total of 35 objects per image. The only exception was the screenings class, which consisted of 30 objects instead of 18, due to their small sizes. For the classes of maize kernels (sound maize; *Fusarium* damage; *Diplodia* damage; water damage; heat damage; rodent damage; and yellow maize), the kernels were first imaged with the germ facing upwards (towards the camera), and a second time with the germ facing downwards (away from the camera). Thus, the germ-up and -down oriented versions of the images consisted of the same kernels in the same positions. This emulated industry grading procedures, where the legislation requires inspection of both sides of a maize kernel. For the foreign matter classes (plant material, wheat, sorghum, soy and sunflower seeds), only the sound maize kernels were orientated as before, but completely different undesirable material objects were used between germ-up and -down versions, as the foreign matter often had no obvious germ. The validation set was acquired in the same manner on new sets of kernels for each of the 13 undesirable material classes.

2.4. Multispectral image analysis

Image correction, segmentation and extraction of spectral information were carried out using the Evince v.2.7.0 (Prediktera, Umeå, Sweden) spectral image analysis software package. The germ-up and -down images for each pair, including sound kernels and one undesirable materials class, were mosaiced and each image mosaic was analysed individually.

2.4.1. Principal component analysis

The image calibration and correction from reflectance to absorbance was done automatically in the Evince software package according to Eq. (1).

$$I_{\lambda,n} = -log_{10}\left[\left(\frac{S_{\lambda,n}-B_{\lambda,n}}{W_{\lambda,n}-B_{\lambda,n}}\right)\right] \tag{1}$$

Where: