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Evaluation of the effect of moisture content on cereal grains by digital image analysis

A.R. Tahir [a], S. Neethirajan [a], D.S. Jayas [a,*], M.A. Shahin [b], S.J. Symons [b], N.D.G. White [c]

[a] *The Canadian Wheat Board Centre for Grain Storage Research, Department of Biosystems Engineering, University of Manitoba, Winnipeg, MB, Canada R3T 5V6*

[b] *Canadian Grain Commission, Grain Research Laboratory, 1404-303 Main Street, Winnipeg, Manitoba, Canada R3C 3G8*

[c] *Agriculture and Agri-Food Canada, Cereal Research Centre, 195 Dafoe Road, Winnipeg, MB, Canada R3T 2M9*

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Abstract

Physical appearance and kernel morphology significantly affect the grade of a harvested crop in addition to other factors such as test weight, percentage of foreign matter and constituent components. Moisture content of grain can potentially affect the physical appearance and kernel morphology. The objective of this study was to evaluate the effect of moisture content on the classification capability of colour, morphology and textural features of imaged grains. Colour images of individual kernels and bulk samples of three grain types, namely Canada Western Amber Durum (CWAD) wheat, Canada Western Red Spring (CWRS) wheat and barley were acquired using a machine vision system. The grain kernels were conditioned to 12%, 14%, 16%, 18% and 20% moisture contents before imaging. Previously developed algorithms were used to extract 123 colour, 56 textural features from bulk sample images and 123 colour, 56 textural, 51 morphological features from individual kernel images. The extracted features were analysed for the effect of moisture content. Statistical classifiers and a back propagation neural network model were used for classifying the grain bulk at different moisture contents. The colour and textural features of bulk grain images were affected by the moisture content more than that of the single kernel images.

Keywords: Moisture content; Wheat kernels; Barley; Colour features; Textural features; Morphological features; Image processing

1. Introduction

Grain inspectors use many factors such as colour, size, shape, hardness, impurity, test weight to determine the grain quality. In addition to the grain kernel composition, the grain shape and size also affect the milling yield and baking quality (CGC, 2006; Marshall, Mares, Moss, & Ellsion, 1986; Schuler, Bacon, Finney, & Gbur, 1995).

Machine vision technology (MVT) is increasingly being used to monitor quality parameters in the grain and food industry. For example, MVT has been used to understand the structure–function relationship in grains, and has the ability to translate data gathered from the image into a better process control. Kernel size, colour, density and size distribution affect the reflectance spectra during optical radiation measurement of the wheat kernels (Watson, Shuey, Barisik, & Dick, 1977; Neuman, Sapirstein, Shwedyk, & Buchuk, 1989). Image analysis based on texture, morphology and colour features of grains is essential for various applications in the grain industry including discrimination of wheat classes, to assess grain quality, and to detect insect infestation. During the past 15 years much research has been conducted in developing algorithms for image processing problems such as grain feature extraction and shape analysis to aid in inspection of grain quality. For practical implementation of image processing algorithms in the grain industry there is a need to understand the effects of moisture content; multiple crop years; same class grain from

* Corresponding author. Address: Canada Research Chair in Stored-Grain Ecosystems, 207 Administration Building, University of Manitoba, Winnipeg, MB, Canada R3T 2N2. Tel.: +1 204 4746860; fax: +1 204 4747568.

E-mail address: digvir_jayas@umanitoba.ca (D.S. Jayas).

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different growing regions on the classification capability of these algorithms. This study focuses on characterizing the effect of moisture content of grain kernels on the variation in the grain features from both individual kernels as well as bulk samples and their effect on classification.

The specific objectives of our study were:

(1) to evaluate the variability in the colour, morphology and textural features of cereal grains due to the change in moisture content of the grain kernels; and
(2) to classify cereal grains at different moisture contents using statistical and artificial neural network classifiers.

2. Materials and methods

2.1. Samples

Canada Western Red Spring (CWRS) wheat, Canada Western Amber Durum (CWAD) wheat and barley grains were used as samples for this study. This study is based on grain samples from a single source and for one crop year. To condition grains to desired moisture contents, the following procedure was used: (1) determine initial grain moisture content (ASAE, 2000), (2) calculate the amount of distilled water to be added to reach the desired moisture content, (3) add distilled water to the grain followed by mixing in a drum mixer for 2 h, and (4) place the grain in plastic bags for 4 d for moisture content distribution. After 4 d the grain moisture content was determined using a standard oven-drying method by drying triplicate samples of wheat at 130 °C for 19 h and for barley at 130 °C and 20 h (ASAE, 2000) and if required, the conditioning process was repeated to ensure that the conditioned samples were at 12%, 14%, 16%, 18% and 20% moisture contents (wet basis). Two groups of samples were selected from each of the above sample set. One for individual kernel imaging and the other for bulk imaging. Three hundred kernels from each grain type and from all moisture contents were selected randomly for imaging in a non-touching fashion under the individual kernel imaging set. To acquire bulk sample images, enough grain was poured into a rectangular plastic dish (10 cm × 7.5 cm × 1.5 cm deep) and excess grain was gently removed by a plastic ruler to have a horizontal grain surface.

2.2. Image acquisition

A high resolution colour camera (Pixelink, model PL-A634, Ottawa, Canada) with a Firewire (IEEE 1394) interface was used to acquire grain images. The acquired images were of 1.3 mega pixel resolution. Four overhead tungsten–halogen bulbs (200 W each) illuminated the sample in reflective mode. Pixelink Capture, commercial software supplied by the camera manufacturer (Pixelink, Ottawa, Canada) was used to acquire images. All the samples were imaged at constant camera settings, i.e., exposure time, saturation and gamma. For the individual kernel imaging set, a total of 4500 kernels (300 kernels × 3 grain types × 5 moisture levels) were imaged separately in a non-touching fashion. For the bulk kernel imaging, a total of 1500 images were obtained by scanning 100 samples for each grain type and at 5 moisture levels.

2.3. Feature extraction

The machine vision algorithms developed by the grain storage research group in the Department of Biosystems Engineering, University of Manitoba were used to extract 179 (123 colour and 56 textural) features from the bulk images and 230 features (123 colour, 56 textural and 51 morphological) features from individual kernel images (Karunakaran et al., 2001; Paliwal, Visen, & Jayas, 2003). The grey level co-occurrence matrix (GLCM) and grey level run length matrix (GLRM) models were used to extract textural features. Grey level co-occurrence matrix provides information about the distribution of grey level intensities, whereas GLRM is a representation of the occurrence of collinear and consecutive pixels of similar grey levels in an object. Mean, variance, and ranges of the red (R), green (G), and blue (B) colour primaries and the derived hue (H), saturation (S), and intensity (I) values of the grain kernels were extracted for colour features. Morphological features from individual kernel images including area, perimeter, major axis length, minor axis length, maximum radius, minimum radius, mean radius, four invariant shape moments, and 20 harmonics of Fourier descriptors (FD) were also extracted. The details of these features and the development of algorithm are given in Karunakaran et al. (2001), Majumdar and Jayas (2000a, 2000b, 2000c, 2000d), Paliwal (2002), Paliwal et al. (2003).

2.4. Classification

The extracted features were grouped into 15 sets (3 grain types and 5 moisture levels) each for individual and bulk sample images. The extracted 179 image features from the bulk sample and the 230 features from the individual kernel image groups were further analysed (Table 1) using the STEPDISC function (SAS, 2000) to determine the features contributing most to the classification. The Wilk's lambda (0.25) and the associated average-squared-canonical correlation were used as the criteria of significance. The linear discriminant and linear parametric classifiers were developed using the DISCRIM procedure (SAS, 2000). The discriminant analysis was used to determine the classification accuracy for all the sets. Classification accuracies were determined by randomly selecting the training and testing sets.

Linear parametric classification accuracies were compared with a four layer back propagation neural network (BPNN). A neural network software package (Neuroshell 2, version 4.0, Ward Systems Group, Frederick, MD)

Table 1
Number of extracted features from the images of individual and bulk grain images before and after STEPDISC

Grain type	Features type							
	Total features				Features after STEPDISC			
	Colour	Morphology	Texture	Total	Colour	Morphology	Texture	Total
Bulk samples								
CWAD	123	–[a]	56	179	29	–[a]	16	45
CWRS	123	–[a]	56	179	39	–[a]	25	64
Barley	123	–[a]	56	179	46	–[a]	10	56
Individual kernel samples								
CWAD	123	51	56	230	27	23	19	69
CWRS	123	51	56	230	24	41	13	78
Barley	123	51	56	230	27	39	19	85

[a] Morphological features were not extracted from bulk images.

was used for this purpose. Four layer perceptron is capable of forming an arbitrarily close approximation to any non-linear mapping given sufficient neurons in the hidden layers (Zhang, Verma, & Kumar, 2004). Five random data sets were created by changing the random seed values from zero to five of the data extraction module of Neuro Shell 2 software. The data set was grouped and a ratio of 60%, 20% and 20% among training, test and validation sets was maintained. A four layer neural network model with default number of neurons in two hidden layers were used in this study. The network training was done on the training group and another group was used as a test set. The third independent group was used for validation after the network was trained. Training was stopped after 1000 epochs. Average classification of five trials was calculated.

Both the statistical and the BPNN models were used for classification of same grain with different moisture content levels.

3. Results and discussion

Representative images from a bulk grain sample and a single kernel sample of CWAD are shown in Fig. 1. For individual kernels, the highest contribution to classification (number of features) is from morphological features followed by colour and texture (Table 1). Similarly the highest contribution is from colour features followed by textural features from the bulk samples. There were 17 common features among the bulk grain images while there are 15 common features among individual images of CWAD, CWRS and barley (Table 2).

The morphological parameters such as area and perimeter with respect to moisture from the single kernel images fail to achieve the desired classification due to lower dis-

Table 2
The extracted common features among CWAD, CWRS and barley kernels at 5 different moisture levels

Bulk grain sample images	Individual kernel sample images
Green variance	Area
Blue variance	Perimeter
H mean	H mean
Blue hist 4	Red hist 11
Blue hist 12	Radial FD 3
Red GLCM variance	Radial FD 9
Red GLCM entropy	Radial FD 10
Red GLCM inertia	Radial FD 18
Green GLCM variance	Peri FD 2
Green GLCM cluster shade	Peri FD 3
Green GLCM entropy	Peri FD 11
Green GLCM inertia	Peri FD 20
Blue GLCM inertia	Green GLRM entropy
Gray GLRM colour non-uniformity	Green GLRM run length non-uniformity
Gray GLRM run length non-uniformity	Green GLRM colour non-uniformity
Red GLRM colour non-uniformity	
Blue GLRM colour non-uniformity	

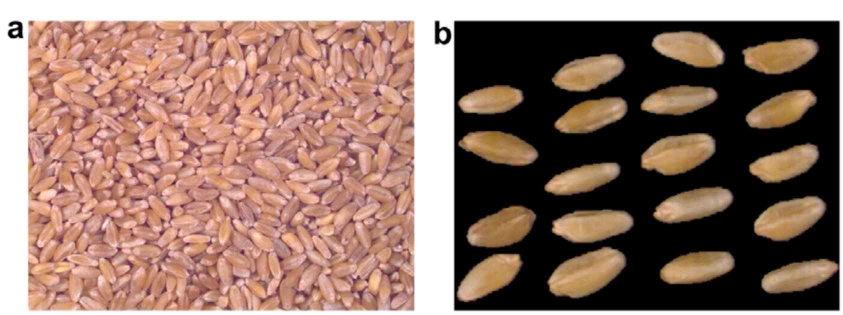

Fig. 1. A representative image of CWAD: (a) bulk grain sample and (b) individual kernel sample.

criminatory power. The original size variation within treatments is greater than variation between treatments (any two moisture contents) from the individual kernel images. For CWAD sample, the pixel value of area is 1254 ± 185, 1292 ± 184, 1306 ± 206, 1360 ± 200, 1370 ± 206 for 12%, 14%, 16%, 18% and 20% moisture contents, respectively. Similar trend was observed for CWRS and barley samples. The top 3 significant features for all five moisture contents for CWAD, CWRS and barley individual and bulk kernel images are shown in Figs. 2 and 3, respectively. Overlap among features in the individual kernel image analysis was higher, but in the bulk kernel image analyses,

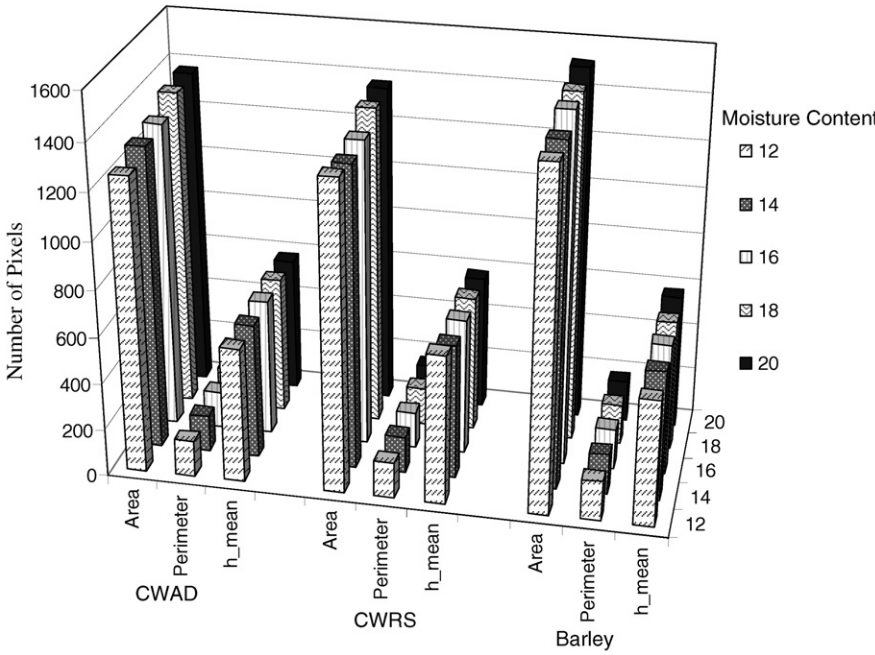

Fig. 2. Data cluster showing top 3 significant features from the CWAD, CWRS and barley individual kernel image analyses at 5 different moisture contents. h_mean is the mean value of hue and represents the dominant wavelength.

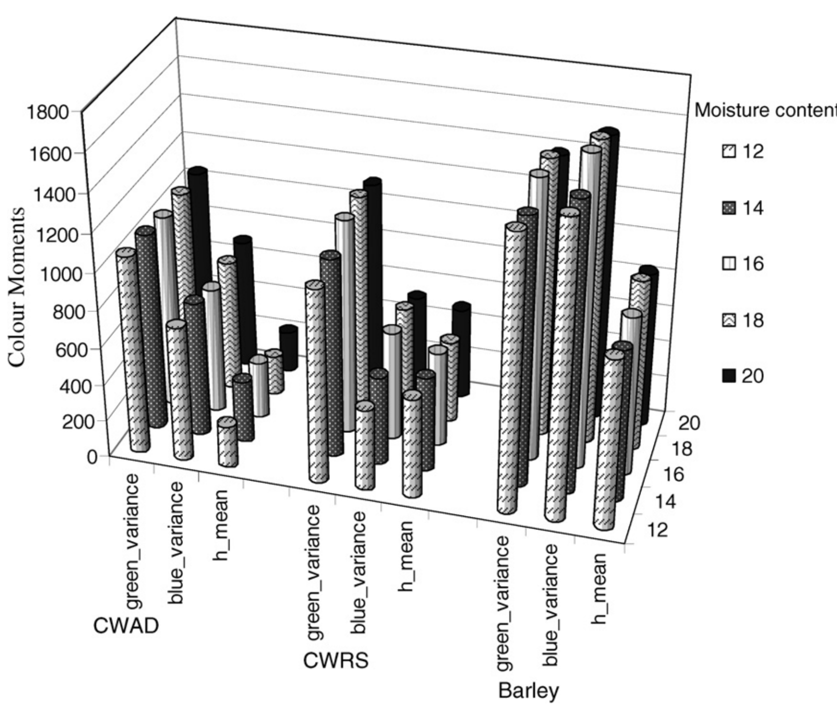

Fig. 3. Data cluster showing top 3 significant features from the CWAD, CWRS and barley bulk kernel image analyses at 5 different moisture contents. h_mean is the mean value of hue and represents the dominant wavelength.

the classes were fairly well separated. Because of the severe overlapping of the same features among different moisture contents in the individual kernel images, the classification is expected to be poor compared to the bulk kernel images.

The colour and the textural features were combined to determine the classification percentages of bulk CWAD, CWRS and barley kernels. The classification accuracies determined using the extracted features by the linear-function parametric statistical classifier and the four layer BPNN of the bulk samples are shown in Table 3. The neural network classifier gave higher classification accuracy than the statistical classifier. A classification accuracy of 90–98% was achieved for all the bulk images using the four layer BPNN model.

Table 3
Classification accuracies of bulk grain sample images using the extracted features after STEPDISC by the linear-function parametric statistical classifier and a four layer BPNN model

Grain type	Linear-function parametric statistical classifier	Four layer BPNN
CWAD 12%	95	98
CWAD 14%	98	97
CWAD 16%	98	98
CWAD 18%	95	96
CWAD 20%	97	98
CWRS 12%	92	95
CWRS 14%	92	94
CWRS 16%	90	92
CWRS 18%	87	90
CWRS 20%	95	98
Barley 12%	90	93
Barley 14%	90	93
Barley 16%	95	98
Barley 18%	92	95
Barley 20%	92	95

Table 4
Classification accuracies of individual kernel images using the extracted features after STEPDISC by the linear-function parametric statistical classifier and a four layer BPNN model

Grain type	Linear-function parametric statistical classifier	Four layer BPNN
CWAD 12%	43	65
CWAD 14%	25	44
CWAD 16%	28	38
CWAD 18%	14	35
CWAD 20%	25	42
CWRS 12%	50	62
CWRS 14%	22	43
CWRS 16%	13	35
CWRS 18%	28	38
CWRS 20%	61	66
Barley 12%	71	68
Barley 14%	63	65
Barley 16%	44	58
Barley 18%	35	46
Barley 20%	52	62

The colour, textural and morphological features were combined to determine the classification percentages of individual CWAD, CWRS and barley kernels. The classification accuracies determined using the extracted features by the linear-function parametric statistical classifier and the four layer BPNN of the bulk samples are shown in Table 4. The classification accuracies for different moisture samples, is lower using the individual kernel image features than using the bulk kernel image features. This implies that the moisture content does not have high impact on the single kernel images but certainly affects the bulk image analysis. Reflected or transmitted light bouncing off the surface of single kernels will leave the surface in different angles in comparison with the light from the bulk kernels. The ratio of reflected light to incident light will be different between single kernel and bulk kernels. Diffusion of reflected light from the bulk kernels will be different because of the layering and packing of kernels.

4. Conclusions

In real time industry applications, grain will be moving in a bulk fashion on the belt under the machine vision camera. The effect of moisture content on individual kernel images was smaller as compared to bulk kernel images. The most contributing parameters for the individual kernel images were morphological followed by colour and textural features. For the bulk images, the colour parameters contributed more than the textural features. Effect of moisture content on individual kernel images needs to be analysed three dimensionally using a higher resolution camera.

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