Classification of cereal grains using a flatbed scanner

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Paliwal, J., Borhan, M.S. and Jayas, D.S. 2004. **Classification of cereal grains using a flatbed scanner**. Canadian Biosystems Engineering/Le génie des biosystèmes au Canada **46**: 3.1 - 3.5. In the quest for an inexpensive machine-vision system (MVS) to identify and classify cereal grains, a flatbed scanner was used and its performance was evaluated. Images of bulk samples and individual grain kernels of barley, Canada Western Amber Durum (CWAD) wheat, Canada Western Red Spring (CWRS) wheat, oats, and rye were acquired and classification was done using a four layer back-propagation neural network. Classification accuracies in excess of 99% were obtained using a set of 10 color and textural features for bulk samples. For single kernel images, a set of at least 30 features (morphological, color, and textural) was required to achieve similar classification accuracies. Classification accuracies for single kernel samples varied between 96 and 99%. **Keywords:** machine-vision system, cereal grains, flatbed scanner, neural network.

Les performances d'un scanner à écran plat pour l'identification et la classification des céréales ont été évaluées dans le cadre du développement d'un système de vision artificielle économique. Des images d'échantillons en vrac et de grains individuels d'orge, de blé Canada Western Amber Durum (CWAD) et de blé Canada Western Red Spring (CWRS), d'avoine et de seigle ont été obtenues à l'aide de cet appareil et une classification a été faite en utilisant un réseau neuronal rétroactif à quatre couches. Le système a permis d'obtenir une précision de classification de plus de 99% en utilisant un groupe de 10 couleurs et textures caractéristiques pour les échantillons en vrac. Dans le cas des images de grains individuels, un ensemble d'au moins 30 caractéristiques (morphologie, couleur et texture) a été requis afin d'atteindre une précision de classification comparable. La précision de classification pour les grains individuels a varié de 96 à 99%. **Mots clés**: système de vision artificielle, céréales, scanner à écran plat, réseau neuronal.

INTRODUCTION

After years of fundamental research work, machine vision technology is slowly making inroads into the grain industry. Commercial systems capable of assisting grain inspectors in grading grain should soon be available to the industry. Canada, which produces and exports billions of dollars worth of grains and oilseeds (hereinafter referred to as grains) every year, will particularly benefit by the advent of such technologies as the grading and classification of grain will become objective and less labor intensive. To accommodate the newer grading techniques, the Canadian Grain Commission has already started a nationwide discussion to introduce a new grain grading system.

The implementation of machine-vision system (MVS) based grading can only be facilitated by the availability of inexpensive and rugged instrumentation. Most of the existing MVSs use charge coupled device (CCD) cameras for image acquisition (Majumdar et al. 1996). Although the performance of CCD cameras has been very satisfactory, their cost and maintenance can be prohibitive for smaller grain handling facilities such as country elevators. Standardization of illumination to be used with these cameras has also remained an unresolved issue (Luo et al. 1997). A desirable MVS should not only be affordable and sturdy but it should also be independent of different lighting sources. As it is impractical to expect exactly similar illumination in different devices or from different light sources, the image analysis software should be written so as to compensate for such inconsistencies.

Researchers have used flatbed document scanners (also called scanners) to address some of the cost and ruggedness related issues associated with CCD cameras (Shahin and Symons 2000). Shahin and Symons (2001) have demonstrated that a scanner based imaging system can be used for classification of lentils. The problem, however, is of calibrating the different makes of scanners and the change in level of illumination of a particular scanner with time. Efforts are being made to derive mapping functions to bring images acquired by different scanners to a common comparable basis. It is hypothesized that the color calibration of different scanners can be incorporated in the software for feature extraction, thus reducing the complexity of the process. The objectives of this study were i) to write a feature extraction software that can compensate for different illumination levels of the imaging system and ii) to use a flatbed scanner to test its feasability to classify bulk samples and individual kernels of barley, Canada Western Amber Durum (CWAD) wheat, Canada Western Red Spring (CWRS) wheat, oats, and rye.

MATERIALS and METHODS

Imaging hardware

The flatbed scanner used in this study was a CanonScan , Model N670U (Canon USA, Inc., Lake Success, NY). The scanner interfaced with a Sony Viao notebook computer (Pentium III, 1.4 GHz) through a universal serial bus (USB) port. The spatial calibration of the scanner was done by scanning a Canadian 10 cent coin, counting the number of pixels in its diameter, and then measuring it with a micrometer (No. 961, Moore and Wright, Sheffield, UK). All the images were acquired at a resolution setting of 300 dpi giving a spatial resolution of 8.5×10^{-2} mm/pixel and were saved in tagged image file (tif) format. Color calibration was done using a Kodak white card with 90% reflectance (E152-7795, Eastman Kodak Co.,

Table 1. Feature sets consisting of all (40), top 20, and top 10 features used as inputs for classification of bulk samples of grain.

	All (20 color and 20 textured) features		Top 20 features	Top 10 features
	Color	Textural		
1	Red histogram range 2	Red GLRM short run	Saturation mean	Saturation mean
2	Red histogram range 3	Blue GLCM cluster shade	Blue GLCM mean	Blue GLCM mean
3	Red histogram range 1	Gray GLRM short run	Blue GLCM cluster shade	Blue GLCM variance
4	Green histogram range 1	Blue GLRM short run	Blue GLCM variance	Blue GLCM correlation
5	Hue mean	Green GCLM cluster shade	Blue GLCM correlation	Green GLCM variance
6	Red histogram range 4	Green GCLM correlation	Green GLCM variance	Red GLRM entropy
7	Saturation mean	Green GLRM short run	Green variance	Green GLCM mean
8	Green variance	Green GLCM variance	Red GLRM entropy	Red histogram range 5
9	Blue histogram range 2	Blue GLCM variance	Red mean	Red histogram range 14
10	Red range	Red GLCM mean	Green GLCM mean	Red GLRM short run
11	Blue histogram range 1	Green GLCM mean	Red histogram range 5	
12	Red histogram range 17	Red GLCM inertia	Green GLCM cluster shade	
13	Blue histogram range 3	Blue GLCM mean	Red GLCM mean	
14	Red histogram range 14	Red GLCM uniformity	Red histogram range 14	
15	Red variance	Blue GLRM long run	Red histogram range 16	
16	Red mean	Green GLCM uniformity	Red histogram range 15	
17	Red histogram range 16	Red GLCM correlation	Green GLCM correlation	
18	Red histogram range 19	Blue GLCM correlation	Green GLCM uniformity	
19	Red histogram range 5	Red GLRM entropy	Red variance	
20	Red histogram range 15	Blue GLCM entropy	Red GLRM short run	

Rochester, NY). Spatial and color calibrations were done prior to starting the image acquisition every day and after taking every five images afterwards. It was decided that correction of R, G, and B components will only be done if the scanner reads them with an error of more than ±5 gray levels.

Grain samples

Composite export samples of barley, CWAD wheat, CWRS wheat, oats, and rye from the growing year 1999 were obtained from the Industry Services Division of the Canadian Grain Commission (Vancouver, BC). Bulk samples were imaged by pouring grain gently on the glass plate of the scanner and then spreading it in a thin layer using a wooden slat. The cover of the scanner was closed and images were acquired. For single kernel images, kernels were put on the scanning surface in a non-touching fashion using a pair of tweezers and then imaged after closing the scanner cover carefully (to minimize the displacement of kernels). For each grain type, eighty four 640 × 480 pixel images of bulk samples were taken. For individual kernels, 900 kernels of each grain type were imaged.

Feature extraction and data analysis

The feature extraction algorithm development was done on an IBM compatible (Pentium III, 450 MHz) computer using Microsoft Visual C++ (Version 6.0) programming language. For color calibration, the algorithm could take any mathematical functional relationship between the actual red (R), green (G), and blue (B) components of color and their corresponding values perceived by the scanner. It could then correct the perceived R, G, and B values according to the functional relationship supplied by the user. The functional relationships between the perceived and the actual color primaries differ from scanner to scanner (Shahin and Symons 2000).

The algorithm extracted 20 color and 20 textural features from bulk sample images (Table 1). These features were the best 40 features obtained from a set of 179 features in a previous study by Visen (2002). For single kernel images, 20 morphological, 20 color, and 20 textural features were used for classification (Table 2). These 60 features were the optimum features taken from a set of 230 features as suggested by Paliwal et al. (2003) in an earlier study. Initially, all the features (40 for bulk sample images and 60 for single kernel images) were used as inputs and classification accuracies were obtained for all the grain types. Features were ranked in descending order of their contribution towards the classification process and the top half of the features were used again for classification. With this new reduced set of features the network was retrained and classification accuracies calculated. The process of keeping the top half features and eliminating the rest was followed until the classification accuracies fell down significantly.

Classification was done using a four layer back-propagation neural network (Jayas et al. 2000, Paliwal et al. 2001). Design and implementation of neural networks was done using the software package NeuroShell 2 (Ward Systems Group, Frederick, MD). The input layer of the network consisted of neurons equal to the number of input features and the output layer had neurons equal to the number of output categories (five categories for five grain types in this case). The number of nodes in the hidden layer was calculated using the formula:

$$n = \frac{I + O}{2} + y^{0.5} \tag{1}$$

where:

n = number of nodes in hidden layer,
I = number of input features,
O = number of output, and
y = number of input patterns in the training set (Ward Systems Group 1998).

Table 2. Feature sets consisting of all (60), top 30, and top 10 features used as inputs for classification of single kernel samples of grains.

	All (20 morphological, 20 color, and 20 textural features)			Top 30 features	Top 10 features
	Morphological	Color	Textural		
1	Perimeter	Red moment 1	Green GLCM mean	Red histogram range 11	Area
2	Mean radius	Red moment 2	Green GLCM cluster shade	Area	Mean radius
3	Area	Green moment 2	Green GLRM run percent	Mean radius	Minor axis length
4	Boundary_FD_2	Blue histogram range 1	Green GLCM variance	Red range	Blue GLRM run percent
5	Minor axis length	Red moment 3	Blue GLCM mean	Red histogram 9	Peri_FD_2
6	Boundary_FD_18	Blue moment 3	Green GLCM correlation	Red histogram 10	Saturation mean
7	Radial_FD_2	Hue mean	Green GLRM long run	Major axis length	Radial_FD_2
8	Radial_FD_3	Blue variance	Blue GLRM color non-uniformity	Peri_FD_18	Peri_FD_12
9	Shape moment 3	Saturation mean	Green GLCM entropy	Blue GLRM run percent	Minimum radius
10	Boundary_FD_5	Blue mean	Green GLRM short run	Minor axis length	Blue GLRM run length non-uniformity
11	Boundary_FD_17	Red histogram range 9	Green GLRM run length non-uniformity	Blue GLRM run length non-uniformity	
12	Shape moment 4	Green variance	Blue GLCM correlation	Peri_FD_2	
13	Radial_FD_5	Red variance	Blue GLRM short run	Maximum radius	
14	Minimum radius	Blue range	Red GLCM homogeneity	Green GLRM run percent	
15	Major axis length	Red histogram range 10	Blue GLCM variance	Perimeter	
16	Boundary_FD_20	Green histogram range 1	Red GLCM variance	Red GLCM homogeneity	
17	Boundary_FD_1	Green moment 1	Gray GLRM run length	Hue mean	
18	Boundary_FD_3	Red range	Blue GLRM run percent	Saturation mean	
19	Maximum radius	Green range	Red GLRM run length non-homogeneity	Radial_FD_2	
20	Boundary_FD_12	Red histogram range 11	Blue GLRM run length non-homogeneity	Blue GLRM color non-uniformity	
21				Green range	
22				Red moment 2	
23				Green GLCM entropy	
24				Green moment 1	
25				Blue range	
26				Green moment 2	
27				Red moment 1	
28				Minimum radius	
29				Peri_FD_12	
30				Boundary_FD_2	

The number of nodes was varied to see any significant improvement in performance. If no improvement was observed, the number of nodes calculated by the formula was used to train the network. Because two hidden layers were used in this study, the number of nodes calculated by the formula was equally divided between them. For training and validating the network, images were divided into three sets of training, testing, and validating sets that consisted of 35, 15, and 50% images, respectively. The network was trained using the training set and tested during its training using the testing set. Once trained, the network's performance was tested on the validating set. A k-cross validation with k=3 was done and average classification accuracies were reported for each grain type.

Testing robustness of algorithm

A small experiment was performed to test the robustness of the written algorithm for its ability to compensate for erroneous R, G, and B values. The bed of the scanner was covered with a fully transparent yellow colored plastic sheet. A Kodak gray scale card (Eastman Kodak Co., Rochester, NY) was scanned and the perceived R, G, and B values for eight known shades of gray were noted. Mapping functions for the actual and the perceived R, G, and B primaries were established. Twenty five kernels (five kernels of each grain type) were glued to a piece of paper and imaged with and without the colored plastic sheet on the scanner bed. The kernels were glued to ensure that they were scanned each time in the same orientation. To correct the color distortion induced by the plastic sheet, the derived mapping functions

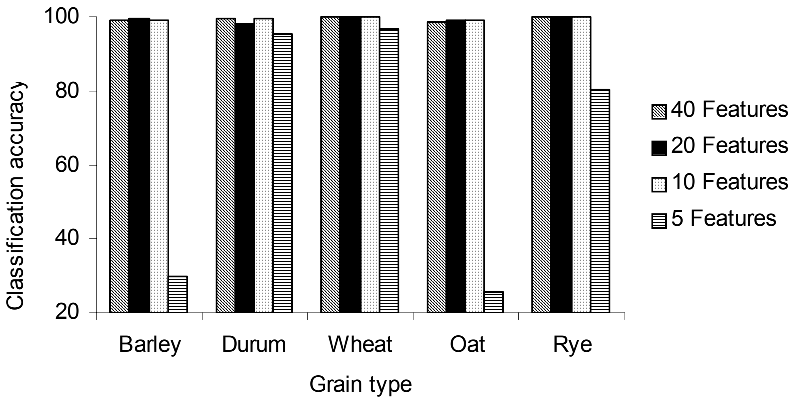

Fig. 1. Classification accuracies of bulk grain samples using input feature sets of 40, 20, 10, and 5 features.

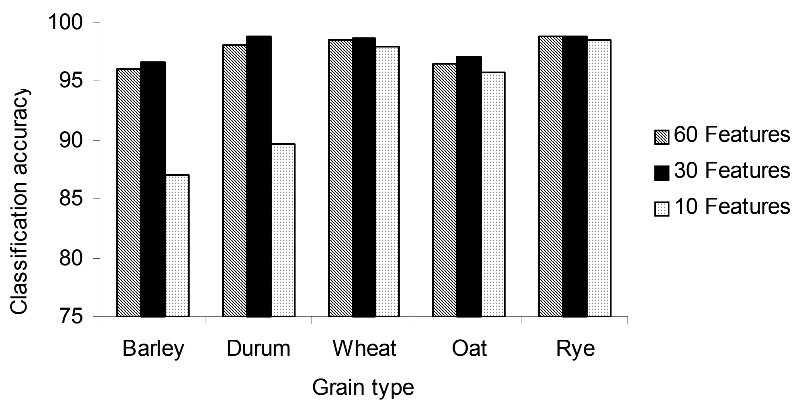

Fig. 2. Classification accuracies of single kernel samples using input feature sets of 60, 30, and 10 features.

for the R, G, and B values were used in the algorithm before extracting the features. For both the images (with and without the colored plastic sheet), color features of corresponding kernels were extracted and compared.

RESULTS and DISCUSSION

Because the plastic sheet was of a uniform color, the mapping functions between the perceived and actual R, G, and B values were linear. When the image acquired through the colored plastic sheet was corrected for color using the algorithm, the means of the R, G, and B values were always within an error range of ±3 gray levels. The range, however, was affected by up to 7%. This may have been because of the fact that the sheet did not allow 100% of the light to pass through it reducing its dynamic range. This scenario is not likely to occur in practice where the kernels are scanned by directly placing them on the bed of the scanner.

For the CanonScan scanner used in this study, color calibrations done at different stages of image acquisition indicated that the gray levels read by the scanner were always within the predefined error range of ±5. Therefore, the color correction module was not required for the bulk and single kernel images that were acquired for feature extraction and classification.

For bulk grain samples, classification accuracies remained above 98% even when the input features were reduced to 10 (Fig. 1). There was no significant difference ($P<0.01$) in the classification accuracies when 40, 20, and 10 features were used as inputs (Fig. 1). Table 1 shows the feature sets with all (40), 20, and 10 features ranked in the order of their contribution to the classification process. Both color as well as textural features were important for classification and all the three color primaries (i.e., R, G, and B) played important roles in characterizing the grains. These results are consistent with earlier studies to classify bulk samples of grains (Majumdar and Jayas 2000; Visen et al. 2002). Performance of the classifier dropped steeply (between 50% and 70% for different grain types) when the input feature set was reduced to five features. This indicates that at least 10 features were required to perform the classification and any further reduction in the number of input features compromised the classification accuracy.

In the case of single kernel samples, classification accuracies were in excess of 96% for all the grain types when 60 features were used as inputs. There was no deterioration in performance of the classifier when the input feature set was halved to 30 (Fig. 2). However, when input features were further reduced to 10, classification accuracies of barley and CWAD wheat reduced significantly ($P<0.01$). Thus, a feature set consisting at least 30 features was necessary to obtain good classification for all the five grain types. Table 2 lists the feature sets with 60, 30, and 10 features that were used for classification. In the reduced feature sets of 30 and 10 features it can be seen that morphological features ranked higher than color and textural features. This result is in agreement with some of the previous studies (Paliwal et al. 2003) that indicated that the shapes and sizes of kernels were more important in characterizing the grains than color or texture.

It was observed that classification accuracies of bulk samples were generally higher than individual grain kernels. The reason can be attributed to the fundamental of image acquisition using a scanner. The sensors of the scanner are designed to scan objects that are in perfect contact with the surface of its glass bed. As we move away from the glass bed, information sensed by the scanner sensors becomes hazy. Therefore, in case of single kernels, due to the thickness of the kernels the entire kernel was not very much in focus. Whereas, while imaging bulk samples the entire surface of the glass bed was covered with grain and hence the images acquired were sharp. Nevertheless, the algorithm's robustness and a well chosen set of features overcame the problem of 'not so sharp' images for single kernels and very high levels of classification could be obtained.

CONCLUSIONS

A very robust algorithm to extract various features from bulk and single kernel samples of grain has been written. The algorithm can compensate for inconsistencies and errors that can occur due to various kinds of illumination devices used in different image acquisition systems. This study has demonstrated that the algorithm can be used with bulk and single kernel images acquired using a flatbed scanner. Classification accuracies in excess of 98% for bulk samples and 96% for single kernel samples were obtained using the devised algorithm in conjunction with a flatbed scanner for five grain types namely, barley, Canada Western Amber Durum (CWAD) wheat, Canada Western Red Spring (CWRS) wheat, oats, and rye. Use of a flatbed scanner instead of a charge coupled device (CCD) camera will help in making machine vision systems more affordable to the grain industry.

REFERENCES

Jayas, D.S., J. Paliwal and N.S. Visen. 2000. Multi-layer neural networks for image analysis of agricultural products. *Journal of Agricultural Engineering Research* 77(2):119-128.

Luo, X., D.S. Jayas, T.G. Crowe and N.R. Bulley. 1997. Evaluation of light sources for machine vision. *Canadian Agricultural Engineering* 39(4):309-315.

Majumdar, S. and D.S. Jayas. 2000. Classification of cereal grains using machine vision. III. Texture models. *Transactions of the ASAE* 43(6):1681-1687.

Majumdar, S., D.S. Jayas, J.L. Hehn and N.R. Bulley. 1996. Classification of various grains using optical properties. *Canadian Agricultural Engineering* 38(2):139-144.

Paliwal, J., N.S. Visen and D.S. Jayas. 2001. Evaluation of neural network architectures for cereal grain classification using morphological features. *Journal of Agricultural Engineering Research* 79(4):361-370.

Paliwal, J., N.S. Visen and D.S. Jayas. 2003. Cereal grain and dockage identification using machine vision. *Biosystems Engineering* 85(1):51-57.

Shahin, M.A. and S.J. Symons. 2000. Comparison of scanners for grain grading by image analysis. ASAE Paper No. 00-3096. St. Joseph, MI: ASAE.

Shahin, M.A. and S.J. Symons. 2001. A machine vision system for grading lentils. *Canadian Biosystems Engineering* 43:7.7-7.14.

Visen, N.S. 2002. Machine vision based grain handling system. Unpublished Ph.D. thesis. Winnipeg, MB: Department of Biosystems Engineering, University of Manitoba.

Visen, N.S., J. Paliwal, D.S. Jayas and N.D.G. White. 2002. Specialist neural networks for cereal grain classification. *Biosystems Engineering* 82(2):151-159.

Ward Systems Group. 1998. NeuroShell 2, Version 4. Frederick, MD: Wards Systems Group.