Image analysis of bulk grain samples using neural networks

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Visen, N.S., Paliwal, J., Jayas, D.S. and White, N.D.G. 2004. **Image analysis of bulk grain samples using neural networks**. Canadian Biosystems Engineering/Le génie des biosystèmes au Canada **46**: 7.11-7.15. Algorithms were developed to acquire and process color images of bulk grain samples of five grain types, namely barley, oats, rye, wheat, and durum wheat. The developed algorithms were used to extract over 150 color and textural features. A back propagation neural network-based classifier was developed to identify the unknown grain types. The color and textural features were presented to the neural network for training purposes. The trained network was then used to identify the unknown grain types. Classification accuracies of over 98% were obtained for all grain types. For example, the results can be used to identify grain types when unloading railcars at a terminal elevator (grain handling facility). **Keywords:** Image processing, cereal grains, classification, identification, machine vision, automation, grain handling

Des algorithmes pour l'acquisition et l'analyse d'images couleurs d'échantillons en vrac d'orge, d'avoine, de seigle, de blé et de blé durum ont été développés. Ces algorithmes ont permis d'extraire plus de 150 couleurs et caractéristiques de texture. Un classificateur construit à d'un réseau neuronal à propagation arrière a été développé pour identifier les types de grains inconnus. Les caractéristiques de couleur et de texture ont été soumises au réseau neuronal à des fins d'entraînement. Le réseau entraîné a ensuite été utilisé pour identifier les types de grains inconnus. Des précisions de classification atteignant plus de 98% ont été obtenues pour tous les types de grains. Les résultats obtenus dans le cadre de cette recherche pourraient par exemple être utilisés pour l'identification des types de grains lors du déchargement de wagons de transport aux élévateurs de terminaux ferroviaires (installations de manutention des grains). **Mots clés**:analyse d'image, grains, céréales, classification, identification, vision artificielle, automatisation, manutention des grains.

INTRODUCTION

Machine vision systems (MVS) provide an alternative to manual inspection of grain samples for kernel characteristic properties and the amount of foreign material. During grain handling operations, information on grain type and grain quality is required at several stages before the next course of operation can be determined and performed. In the present grain-handling system, grain type and quality are rapidly assessed by visual inspection. This evaluation process is, however, tedious and time consuming. The decision-making capabilities of a grain inspector can be seriously affected by his/her physical condition such as fatigue and eyesight, mental state caused by biases and work pressure, and working conditions such as improper lighting, climate, etc.

Determining the potential of morphological features to classify different grain species, classes, varieties, damaged grains, and impurities, using statistical pattern recognition techniques, has been the main focus of much of the published research (e.g. Neuman et al. 1987; Keefe 1992; Barker et al. 1992a, 1992b, 1992c, 1992d; Sapirstein and Kohler 1995; Majumdar and Jayas 2000a). Some researchers (Neuman et al. 1989a, 1989b; Luo et al. 1999a; Majumdar and Jayas 2000b) have tried to use color features for grain identification. Only limited work has been done to incorporate textural features (e.g. Majumdar et al. 1996; Majumdar and Jayas 2000c, 2000d) for classification purposes. Efforts have also been made to integrate all these features in terms of a single classification vector (Paliwal et al. 1999) for grain kernel identification.

Most of the published research focuses on identifying a grain type from digital images acquired by placing kernels in a non-touching fashion. Such experiments are comparatively easier to perform in controlled situations, such as a research lab, but would be difficult to implement on site because of cumbersome setup requirements. Such systems generally require a device to present kernels in a non-touching manner, an independent conveyor belt assembly, and the typical imaging devices in order to perform in real-time. Also, the algorithms for classification of grain type used with such images are based on morphological, color, and textural features, combined. The pre-processing operations such as segmentation, background removal, and object extraction, which are a prerequisite to determining morphological features, are some of the most time-consuming operations. On the other hand, if the grain type can be determined using images of bulk samples, many of the requirements of the previously described system become redundant. The imaging devices can be mounted at the site and will not require a grain separation device. The image of bulk sample may be acquired by creating a flat layer of grain on a conveyor belt. Moreover, an image of a bulk sample does not contain individual objects in it, so it does not need to be pre-processed for background removal and object extraction. The grain type classification using images of bulk samples can be attempted using just color and textural features and results of such classification can be used for the automation of rail car unloading operations at grain handling facilities. Currently, we are designing a "Grainobot" to unload rail cars and quick identification of grain type is a part of its design.

Previous research suggests that a back propagation neural network is best suited for classification of cereal grains (Jayas et al. 2000). Based on that, the objective of this research was to evaluate a back propagation neural network based classifier for classification of various types of cereal grains using color and textural features extracted from images of bulk grain samples.

Fig. 1. Image acquisition setup and a representative image of bulk Canada Western Amber Durum wheat.

MATERIALS and METHODS

Grain samples

The grain samples used in this study were collected from six locations in Manitoba, 10 locations in Saskatchewan, and seven locations in Alberta for the growing year 1999. The Industry Services Division of the Canadian Grain Commission (Winnipeg, MB) provided the grain samples that were collected at terminal elevators from incoming railcars. The choice of locations was based on climatic subdivisions of the Canadian Prairies (Putnam and Putnam 1970). The selected locations represent five sample locations from the humid prairie, five locations from the semi-arid region, six locations from the sub-humid prairie, and seven locations from the sub-boreal region. Not all grain samples were collected from every location due to non-availability of samples from that location. Grain samples were collected for barley (20 locations), Canadian Western Amber Durum (CWAD) wheat (19 locations), Canadian Western Red Spring (CWRS) wheat (22 locations), oats (16 locations), and rye (14 locations).

The grain for bulk sample images was obtained by pouring 2 kg of grain kernels into a large plastic bag and shaking it to mix the grain thoroughly. The grain was then slowly poured into a petri dish until it was completely filled. The excess grain was gently shaken off the petri dish so that the top level of grain was almost horizontal and matched up to the rim of the petri dish. This process was repeated 45-75 times for each growing location using fresh samples each time. Thus, a total of 5000 images of bulk samples were acquired (1000 images of each grain type). After imaging, the grain kernels were sealed in a plastic bag, labeled with relevant information such as growing location, growing year, date of image acquisition, etc., and stored for future reference.

Image acquisition device

For image acquisition, a 3-chip charge-coupled device (CCD) color camera (DXC-3000A, SONY) was used (Figure 1). The camera had a zoom lens (VCL-1012 BY, SONY) of 10-120 mm focal length and a close-up lens set (72 mm, The Tiffen Company, Hauppauge, N.Y.). The camera was connected to a personal computer (PC) (PIII 450 MHz) with a color frame grabbing board (Matrox Meteor-II multi-channel, Matrox Electronic Systems Ltd., Montreal, QC). To provide rigid stable support and easy vertical movement, the camera was mounted on a stand (M3, Bencher Inc., Chicago, IL). The camera was connected to a camera control unit (CCU-M3, SONY). A fluorescent tube with a 305 mm diameter 32-W circular lamp (FC12T9/CW, GE Lighting) with a rated voltage of 120 V was placed around and just below the surface level of the sample placement platform of the light chamber. A light diffuser, a semi-spherical steel bowl of 390 mm diameter, covered the light bulb and the object plane so that the object plane was only exposed to the diffused light. The inner side of the bowl was painted white and smoked with magnesium oxide. The 72-mm close-up lens was used to achieve a spatial resolution of 0.064 mm/pixel in horizontal and vertical directions. The images acquired were 640 x 480 pixels in size. The image acquisition procedure, system calibration, details of the features, and the algorithm used to extract the features have been described in detail by Karunakaran et al. (2001). A total of 179 features (123 color and 56 textural) were extracted from each image using the developed algorithm.

Classification models

A database of color and textural features was created for each category (barley, CWAD wheat, CWRS wheat, oats, and rye) using 1000 images of each grain type, selected randomly from the different growing regions. The classification study was carried out using five different types of feature sets. The first two sets consisted of 123 color and 56 textural features, respectively. The third set consisted of all the color and textural features combined, i.e., a total of 179 features. The fourth and fifth sets were subsets of the third set. They consisted of the top 10 and the top 20 color and textural features combined, thus having a total of 20 and 40 features, respectively. The top 10 and top 20 features were determined from studies using the color and textural feature models. These feature sets were called combined 40 and combined 20 feature sets. All five data sets were split into five subsets for cross validation analysis.

Classifiers

A neural network architecture was designed and implemented using the software package NeuroShell 2 (Ward Systems Group, Frederick, MD). Jayas et al. (2000) indicated that a back propagation network (BPN) is best suited and thus is the most popular choice for classification of agricultural produce. A four-layer BPN was used for cereal grain classification. The data were compiled only for BPN so that the results could be compared to a previous study by Majumdar and Jayas (1999) in which they reported classification results using non-parametric statistical classifiers. The network used logistic scaling and activation functions at input and processing levels, respectively. It consisted of up to 179 input nodes (number of input nodes equals number of input features used), 106 hidden nodes in two hidden layers, and five output nodes, one for each grain type. The number of hidden nodes was automatically calculated by

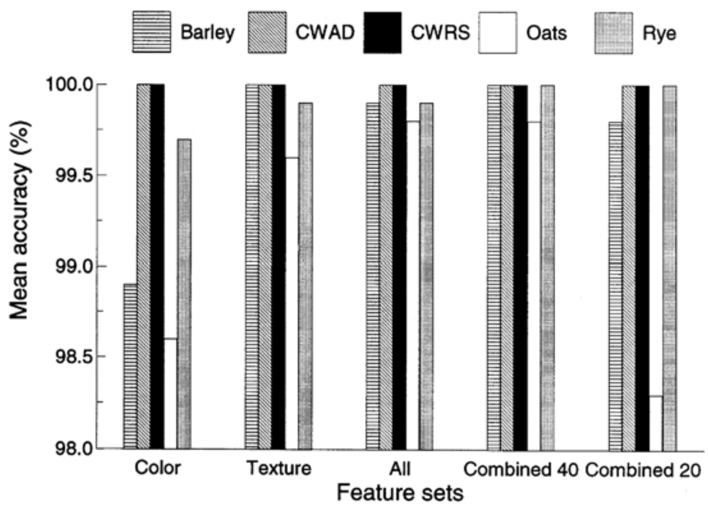

Fig. 2. Classification accuracies of cereal grains using different input feature sets.

the Neuroshell software using the equation:

$$N = \frac{I + O}{2} + y^{0.5}$$

where:
N = number of hidden nodes,
I = number of input nodes,
O = number of output nodes, and
y = number of training patterns.

Training, testing, and validation of neural networks were performed using 5000 bulk sample images (1000 of each grain type). Training, testing, and validation was performed five times using different data sets. Each of the training and testing data sets consisted of 250 images (50 of each grain type) whereas the validation data set consisted of 4500 images (900 of each grain type). The network was trained and tested for 1000 epochs and was then applied to the validation data set. The number of epochs was kept at 1000 to allow sufficient events before the training was stopped. If the minimum error value of the network remained unchanged for 20 training generations, the training was automatically stopped. Over-training of the network was prevented by automatically saving the network for the epoch that resulted in minimum error for the testing data set. Over-training starts to occur when the minimum error for training network continues to drop whereas the minimum error for testing network reverses its direction and starts to increase.

Table 1. The top 20 color and textural features from the color and textural features models, respectively, based on their respective contribution towards classification accuracy for cereal grains while using a back propagation network classifier.

Rank	Feature sets	
	Color	Textural
1	Red histogram range 2	Red GLRM short run
2	Red histogram range 3	Blue GLCM cluster shade
3	Red histogram range 1	Gray GLRM short run
4	Green histogram range 1	Blue GLRM short run
5	Hue mean	Green GLCM cluster shade
6	Red histogram range 4	Green GLCM correlation
7	Saturation mean	Green GLRM short run
8	Green variance	Green GLCM variance
9	Blue histogram range 2	Blue GLCM variance
10	Red range	Red GLCM mean
11	Blue histogram range 1	Green GLCM mean
12	Red histogram range 17	Red GLCM inertia
13	Blue histogram range 3	Blue GLCM mean
14	Red histogram range 14	Red GLCM uniformity
15	Red variance	Blue GLRM long run
16	Red mean	Green GLCM uniformity
17	Red histogram range 16	Red GLCM correlation
18	Red histogram range 19	Blue GLCM correlation
19	Red histogram range 5	Red GLRM entropy
20	Red histogram range 15	Blue GLCM entropy

GLRM - gray-level run length matrix
GLCM - gray level co-occurrence matrix
Details of the features are given in Karunakaran et al. (2001).

RESULTS and DISCUSSION

Analysis using color features

The feature set used consisted of 123 color features. A four-layer BPN was used to develop a classifier. It consisted of 123 input nodes, 39 nodes in each of the two hidden layers, and five output nodes, one for each grain type. The summarized results of color analysis are shown in Figure 2. The classification accuracy was very high throughout the five trials using the color features alone. The network calculated the contribution factor of each input feature and the average contribution of these features over five trials was used to determine the top 20 color features. Table 1 gives the top 20 features ranked in order of their decreasing contribution to the classification process. The contribution list shows that most of the color features come from the red band of the bulk sample images.

Analysis using textural features

A four-layer BPN was used for classification using textural features. The network consisted of 56 input features, 22 nodes in both hidden layers and five output nodes, one for each grain type. The summarized results of textural analysis are shown in Figure 2. Table 1 gives the top 20 textural features ranked in order of their decreasing contribution to the classification process. All the color bands and a combination (gray band) are present in the top five textural features. The features, short run and cluster shade, appear three and two times, respectively, in the first five features. Similar to classification accuracies obtained using color features, the classification accuracies were very high using textural features.

Analysis using all features

The color and textural feature sets were combined to form the all-features set that consisted of 179 input features. A four-layer BPN was used to develop a classifier. It consisted of 179 input

Table 2. The top 40 features from the all-features model based on their respective contribution towards classification accuracy for cereal grains in bulk sample images while using a back propagation network classifier.

Rank	Features	Rank	Features
1	Red histogram range 3	21	Blue GLCM cluster shade
2	Gray GLRM short run	22	Red GLCM mean
3	Blue GLRM short run	23	Green GLRM long run
4	Red histogram range 1	24	Blue histogram range 2
5	Red GLRM short run	25	Red histogram range 14
6	Red histogram range 2	26	Blue mean
7	Green GLRM short run	27	Red histogram range 20
8	Hue mean	28	Red histogram range 21
9	Green GLCM inertia	29	Blue GLRM long run
10	Gray GLRM color non-uniformity	30	Blue GLCM entropy
11	Red histogram range 4	31	Green GLCM uniformity
12	Blue GLRM color non-uniformity	32	Green histogram range 1
13	Red GLRM long run	33	Red moment 1
14	Red GLRM color non-uniformity	34	Red GLCM uniformity
15	Red mean	35	Blue GLCM uniformity
16	Saturation mean	36	Hue range
17	Red GLCM inertia	37	Gray GLRM long run
18	Gray GLRM entropy	38	Red histogram range 19
19	Gray GLCM mean	39	Gray GLCM homogeneity
20	Blue GLRM runpercent	40	Blue GLCM correlation

GLRM - gray-level run length matrix
GLCM - gray level co-occurrence matrix
Details of the features are given in Karunakaran et al. (2001).

nodes corresponding to 123 color features and 56 textural input features. The two hidden layers consisted of 53 nodes each and output layer consisted of five nodes, one for each grain type. The summarized results of the all-features analysis are shown in Figure 2.

The classification accuracy, as expected, was very high for all the grain types. Table 2 lists the top 40 features based on their respective contribution towards classification accuracy. It can be seen that both color and textural features appear in the list and are equally important towards classification of bulk sample images. Most of the color and textural features present in Table 1 are also present in Table 2, however, some of the features are missing altogether. The relative rankings of the features from Table 1 are somewhat different from those in Table 2. This is because excessive number features adversely affect on the classifier by introducing redundancies and increasing its complexity (Luo et al. 1999b). As a result, a useful feature may get over-shadowed by other features and may not contribute as much in presence of certain input features.

Analysis using the combined 40 features set

The feature set used consisted of the top 20 color and the top 20 textural features. A four-layer BPN was used to develop a classifier. It consisted of 40 input nodes, 18 nodes in both hidden layers and five output nodes, one for each grain type. The summarized results of the combined 40 model are shown in Fig. 2. Since the accuracy was very high, the number of inputs was lowered to 10 each from color and textural features sets to determine classification accuracy using a reduced feature set.

Analysis using the combined 20 features set

A four-layer BPN was used to develop the classifier for analysis using combined 20 features set. The input to the network consisted of the top 10 color and the top 10 textural features. The two hidden layers consisted of 14 nodes each, output layer consisted of five output nodes, one for each grain type. The summarized results of combined 20 feature model are shown in Figure 2. Even though the number of inputs was greatly reduced, the classification accuracies still remained very high for all the grain types.

Majumdar and Jayas (1999) reported classification accuracies close to 100% using images of bulk samples. Although the classification accuracies obtained using neural networks are similar to those obtained using a statistical classifier, the ranking of color and textural features for classification is quite different. The results from this study can be used for rapid identification of grain types when they arrive in railcars at the terminal grain elevators. A grain sample can be collected in a tray and the bulk sample image can be acquired. The information from an MVS can then be used to match the information from the rail company before dumping the grains into the pit for proper binning. Since this classification technique does not require time consuming image processing routines such at segmentation and Fourier descriptors, it can readily be implemented using commercial imaging libraries with DSP boards for real time operations.

The classification accuracy for identifying a grain type for certain handling and storage purposes need not to be as high as the results obtained in this study. Repeated measurements from multiple images acquired on a moving conveyor belt can be performed to improve the confidence in decision making. For example, if 10 images were acquired and 9 were correctly classified, then it can be concluded that the sample is of that particular grain type. In this example 90% accuracy would be acceptable. The images in this study were acquired from clean grain samples. For future study, the effect of percentage of foreign material on classification accuracy can be investigated using images of bulk samples.

CONCLUSION

The first three histograms from the red band and short run from all the color bands were the most important color and textural features, respectively. The classification accuracies obtained using different input feature sets for all grain types were over 98%. Best results were obtained using the combination of both color and textural features. Other than oats, all the grain types could be classified with close to 100% classification accuracy using just the combined 20 features set.

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