DOCKAGE IDENTIFICATION IN WHEAT USING MACHINE VISION

A Thesis
Submitted to the Faculty of Graduate Studies
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by

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Dedicated to my beloved parents

ABSTRACT

Algorithms were developed to classify dockage components from Canadian Western Red Spring (CWRS) wheat and other cereal grains like durum wheat, barley, rye, and oats based on morphological and color features. The dockage classes used were: wheat heads, chaff, wildoats, canola, wild buckwheat, flax, and broken-wheat pieces. The wheat head dockage class was subdivided into single and multiple wheat heads to improve the classification accuracy.

The developed algorithms were tested on images taken with an area scan camera. Training and test data sets were established to evaluate the classification accuracies based on the extracted features.

Morphology-color, morphology, and color models were evaluated for classifying the dockage components. Morphology-color model gave 90.9 and 99.0% mean accuracies when tested on the test and on the training data sets, respectively. The mean accuracies of 90.5 and 98.7% were obtained when the first 15 features from the morphology-color model were used on the test and on the training data sets, respectively. The mean accuracies of 89.4 and 96.3% for the morphology model and 71.4 and 75.6% for the color model were achieved when tested on the test and on the training data sets, respectively.

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LIST OF ABBREVIATIONS

CWRS	Canada Western Red Spring
HRW	Hard Red Winter
SWS	Soft White Spring
SWW	Soft White Winter
CPS	Canada Prairie Spring
PSI	Particle size index
R	Red
G	Green
B	Blue
H	Hue
S	Saturation
I	Intensity
RGB	Red-green-blue
HSI	Hue-saturation-intensity
FOV	Field of view
Npar	Non-parametric estimation
M-whead	Multiple wheat head
S-whead	Single wheat head
W-bwheat	wild buckwheat

CHAPTER 1: INTRODUCTION

Canada produced an average of 55 Mt (million tonnes) of grains and oilseeds worth about 6 billion dollars annually during the years from 1983 to 1992 (Canada Grains Council 1994). About 70% of these grains are exported through a grain collection, handling, and shipping system. The producers store their grain on farms and usually deliver it in farm-trucks to primary (country) elevators (grain handling facilities). Grain moves from the primary elevators to terminal elevators by train.

A machine vision system (MVS) could be used effectively for objective measurement of physical quality parameters of the grain at terminal elevators. The primary reason for its potential application for wheat inspection at terminal elevators lies in its capability to quantify (with precision, speed, and consistency) the composition and physical characteristics of grain samples using parameters which form the basis of visual inspection (e.g. object size, shape, colour, reflectance, and texture) (Sapirstein and Bushuk 1989). Moreover, powerful microcomputers and specialized hardware have fostered moderately priced, high performance machine vision systems able to handle the wide variability in size, shape, colour, and textural characteristics of agricultural produce and products. As a result, the MVS offers the potential to improve the competitive position of agriculture by raising product quality while lowering processing costs.

Fast and accurate information on the contents of a grain sample can be used to increase the efficiency of most grain handling operations (such as grain unloading, cleaning, binning, and shipping) at terminal elevators (Shatadal et al. 1995b). The important applications of machine vision to the grain industry include the design and development of an objective, fast, and reliable on-line monitoring system for grain in continuous flow at many points in a terminal elevator (grain handling facility). This would lead to increased cleaning throughput and enhanced recovery of salvageable grains. Use of machine vision guided controls and robotics could lead to complete automation of modern terminal elevators. A commercial MVS for grain inspection at terminal elevators is not yet available. Although substantial efforts have been made in the last decade on using MVS for automatic information acquisition on the content and quality of grain samples (Barker et al. 1992a, 1992b, 1992c, 1992d; Chen et al. 1989; Ding et al. 1990; Draper and Travis 1984; Hehn and Sokhansanj 1990; Keefe 1992; Keefe and Draper 1986; Kohler 1991; Lai et al. 1986; Majumdar et al. 1996a, 1996b; Myers and Edsall 1989; Neuman et al. 1987, 1989a, 1989b; Sapirstein and Bushuk 1989; Sapirstein et al. 1987; Shatadal et al. 1995a, 1995b; Symons and Fulcher 1988a, 1988b; Thompson and Pomeranz 1991; Travis and Draper 1985; Zayas et al. 1985, 1986, 1989, 1990), many of the special needs and problems involved in industrial application are still unresolved. Dockage identification is one of these needs.

Dockage is a material that is removed from the grain by using approved cleaning equipment so that grain can be assigned the highest grade for which it qualifies (Anonymous 1994). At terminal elevators grain is received in railcars and the varying amounts of dockage is removed by mechanical separators before the grain is stored for shipping to export buyers. A series of cleaning machines are used to remove the dockage. Export shipments are the combined grain from several storage bins of like type and grade that meet the buyers' specifications for quality and grade specifications. The dockage in the grain (wheat) has to be identified for effective automation. The dockage in wheat is assessed by separating the dockage from the grain by a Carter dockage tester or Emersion kicker (Anonymous 1994). For the salvageable grain recovery and for adjusting the efficiency of the cleaning machines. dockage tester fractions have to be identified. With the present machine vision technology. the car contents can be identified and recognized as wheat, barley, durum, rye, and oats. and the clean samples can be identified with reasonable accuracy (>95%). So far no work has been reported on dockage identification in wheat using machine vision.

The objectives of my thesis research were:

(i) to use machine vision system to identify dockage in wheat by developing software to extract morphological and limited colour features from grain kernels and from dockage components,

(ii) to investigate the potential of different image-extracted morphological and colour features for classification of dockage components from CWRS wheat and from other cereal grains such as durum wheat, barley, rye, and oats, and

(iii) to investigate the feasibility of classifying dockage components into their appropriate classes using the selected features by designing or selecting appropriate statistical pattern classifiers.

CHAPTER 2: MACHINE VISION

A machine vision system (MVS) consists of imaging hardware and processing software. The elements of a general purpose MVS (Fig 2.1) are: (i) image acquisition, (ii) storage, (iii) processing, (iv) communication, and (v) display.

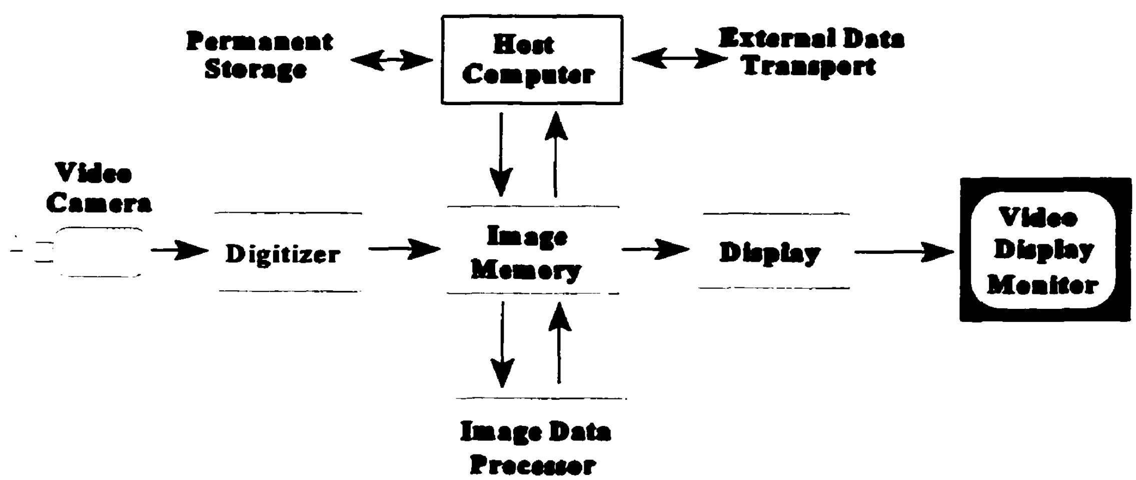


Fig 2.1. Schematic of a typical machine vision system

2.1 Image Acquisition

Two elements are required to acquire digital images. The first is a physical device (e.g. video camera) that is sensitive to a band in the electromagnetic energy spectrum (such as X-ray, ultraviolet, visible, or infrared bands) and that produces an electrical signal output proportional to the level of energy sensed. The second, called a digitizer, converts the electrical output of the physical sensing device into digital form (Gonzalez and Woods 1992).

2.2 Storage

Providing adequate storage is usually a challenge in the machine vision systems because a single 8-bit image of 1024 x 1024 pixels requires 1 Mb of storage. Digital data storage in the MVS are of three types: (i) short term storage for use during processing, (ii) on-line storage for relatively fast recall, and (iii) archival storage. For the short term storage, computer memory or specialized boards called frame buffers are used. On-line storage generally takes the form of magnetic disks. A Magneto-optical (MO) disk stores a gigabyte of information. Archival storage is characterized by massive storage requirement and magnetic disks and optical disks are used for such storage.

2.3 Image Processing

2.3.1 Digital Image The term image refers to a two-dimensional light intensity function, denoted by f (x, y), where the value or amplitude of 'f' at spatial coordinates (x, y) gives the intensity (brightness) of the image at that point. To be suitable for computer processing, an image function f (x, y) must be digitized both spatially and in amplitude. Digitization of spatial coordinates (x, y) is called image sampling, and amplitude digitization is called the grey-level quantization. Suppose that a continuous image f (x, y) is approximated by equally spaced samples arranged in the form of an N x M array, where each element of the array is a discrete quantity, i.e.:

$$f(x, y) = \begin{vmatrix} f(0,0) & f(0,1) \ldots & \ldots & \ldots f(0, M-1) \\ \ldots & \ldots & & \ldots \\ f(N-1, 0). & \ldots & \ldots & \ldots f(N-1, M-1) \end{vmatrix} \quad (2.1)$$

The right side of the Eq. #2.1 is called a digital image. In the case of a colour image, the amplitude is a vector which has three components that are either Red, Green, and Blue or Hue, Saturation, and Intensity.

Processing of digital images involves procedures that are usually expressed in algorithmic form. Therefore, with the exception of image acquisition and display, most image processing applications can be implemented in the software. The image processing can be subdivided into three groups: (i) image pre-processing, (ii) image analysis, and (iii) image interpretation.

2.3.2 Image Pre-processing Image pre-processing is improving the image quality either for a better (subjective) interpretation of the image by a human or for making the image more suitable for subsequent steps in computer processing. Noise filtering, contrast enhancement, and image smoothing are some of the pre-processing operations. Because an image is a 2-D signal, image pre-processing concepts require the knowledge on 2-D signal processing.

2.3.3 Image Analysis Image analysis is extracting information from the image for a given application. The image analysis is explained in detail in Chapter 6.

2.3.4 Image Interpretation Image interpretation is making a decision about the image to attain the solution of a given problem based on the information derived from the image. Image interpretation involves image-based knowledge manipulation including procedural or rule based manipulation of image data, 3-D modelling, and hierarchical image analysis. A great amount of non-image related knowledge underlying the scene representation may have to be used in image understanding. Artificial neural networks are extensively used in image interpretation and pattern recognition problems.

2.4 Communication

Communication in digital image processing involves local communication among image processing systems and remote communication from one point to another, typically in connection with transmission of image data. Hardware and software for local communication are readily available for most computers. Communication across vast distances presents a more serious challenge if the intent is to communicate image data rather than abstract results. Since most of the machine vision applications are in automated product inspection (exception Satellite MVS), vast-distance communication is not that important.

2.5 Display

The principal display devices used in the modern MVS are monochrome and colour TV monitors. Monitors are driven by the output(s) of a hardware image display module in the back plane of the host computer or as part of the hardware associated with an image processor. The signals at the output of the display module can also be fed into an image recording device (such as slides, photographs, or transparencies) that produces a hard copy of the image being viewed on the monitor screen. Other display media include random-access cathode ray tubes (CRTs) and printing devices.

CHAPTER 3: REVIEW OF LITERATURE

3.1 Background

Though a commercial machine vision system for grain grading and inspection is not yet available, rapid and substantial research has been conducted over the last decade towards building a machine-vision based grain-grader. But many of the special needs and problems in applying machine vision techniques to build a grain grader have yet to be solved. Agrovision AB(S-223 70 Lund, Sweden) has developed a machine to classify wheat, barley, oats, rye, and triticale but its classification accuracy is not reported in the literature. Determining the potential of morphological and colour features to discriminate different grain species, classes, varieties, damaged grains, and impurities using statistical and artificial neural networks pattern recognition techniques has been the main focus of the reported research. This chapter briefly reviews the published research in applying machine vision techniques to the grain industry.

3.2 Potential for Objective Wheat Grading

The primary and export grade determinants of CWRS wheat are given in Appendix A. For primary grades, the maximum tolerances of foreign materials including other cereal grains are 0.75, 1.5, 3.5, and 10% for grade 1, grade 2, grade 3, and feed grade of CWRS wheat, respectively. In the export grades, the maximum tolerances of foreign materials including other cereal grains are 0.4, 0.75, 1.25, and 5% for grade 1, grade 2, grade 3 , and feed grade of CWRS wheat, respectively. The primary grade tolerances for wheat of other classes are 3, 6, and 10% for grade 1, grade 2, and grade 3, respectively. For export grade, these tolerances are 1.5, 3, and 5%, respectively. Tolerances for damaged kernels are also different. The differences in the tolerances for primary and export grades necessitate that grain be processed at some point in the grain distribution chain. In Canada, grain is processed at terminal (export) elevators. To meet these tight tolerances, an objective grain grading system must achieve a near perfect classification of cereal grains and impurities (i.e., CWRS wheat, durum wheat, barley, rye, oats, and dockage and foreign material). Several researchers (Barker et al. 1992a, 1992b, 1992c, 1992d; Draper and Travis 1984; Keefe 1992; Keefe and Draper 1986, 1988; Kohler 1991; Lai et al. 1986; Myers and Edsall 1989; Neuman et al. 1987; Sapirstein and Bushuk 1989; Sapirstein et al. 1987; Symons and Fulcher 1988a, 1988b; Travis and Draper 1985; Zayas et al. 1985, 1986, 1989) applied machine vision and pattern recognition techniques to derive characteristics of cereal grains that can be used for objective grading. Most of these studies were conducted with limited sample size. Also, the method of sample presentation to the field of view (FOV) of the camera was not industrially implementable.

Most of the researchers conducted their studies using morphological features for cereal grain classification. Very limited work has been reported on cereal grain classification using colour features and no work (to the best of my knowledge) has been published on the potential of applying MVS for dockage identification in wheat.

3.2.1 Early Investigations

As mentioned earlier, the investigations related to the application of MVS to the agricultural industry is a few decades old. Segerlind and Weinberg(1972) laid the basis for applying MVS to the grain industry. Though they didn't use any machine vision hardware. they traced the kernel profile on the grid paper to get the image and then estimated grain shape by Fourier series expansion of the radial distance from the centre of gravity to the periphery of the kernels. There was 1% error in separation of oats and barley, and wheat and rye based on the extracted shape features. The class [e.g. Hard Red Spring (HRS), Hard Red Winter (HRW), Amber Durum (AD), Soft White Spring (SWS), Soft White Winter (SWW), Canada Prairie Spring (CPS), and utility and feed wheat are different classes of Canadian wheat] discrimination for wheat was partially successful with 11-25% error.

Draper and Travis (1984) and Travis and Draper (1985) first used the MVS to identify seeds of cereals, fodder plants, and oil and fibre vegetables. They reported that 5 of the crop species could be distinguished from their major contaminants with an overall accuracy of 95% and most of the weed species could be distinguished from each other.

The potential of image analysis for identifying grains of 5 U. K. wheat cultivars on the basis of size and shape was investigated by Keefe and Draper (1986, 1988). In their study, individual seeds resting horizontally, adaxial surface lowermost (i.e., crease down position), and embryo in a fixed position were viewed in side elevation using transmitted light. Nine parameters describing seed shape were used to characterize 400 wheat seeds.

Zayas et al. (1986) used some of the morphological features used by Keefe and Draper (1986) and some additional features to differentiate among individual kernels of different American wheat classes and varieties. For different wheat classes and varieties, the average percentage of correctly classified kernels were 77 and 85%, respectively. They used mainly pair-wise discriminations. The work was limited to a single kernel per image frame and it was necessary to immobilize kernels in a fixed orientation prior to analysis.

Lai et al. (1986) used a pattern recognition technique for identifying and classifying cereal grains. They developed patterns for 6 grains (corn, soybean, sorghum, rice, barley, and wheat) and tested the patterns for their accuracy in recognizing grains. In addition, they applied the technique to differentiate between brown and white rice and to differentiate the sphericity of corn kernels.

3.2.2 Towards A Grain Classifier

After getting positive results from the early investigations, researchers started their investigations towards building a grain classifier. Potential of additional (new) morphological features for grain classification, application of the techniques of the early investigations to other grain types, potential of colour features in grain classification, and solutions to special problems and needs like discriminating the broken kernels from the whole kernels, identification of foreign material were the improved objectives of the continued research in this field.

Neuman et al. (1987) studied the objective classification of Canadian wheat cultivars based on kernel morphology using digital image analysis. They used 576 kernels of pedigreed seed of 14 wheat varieties for analysis. Using a transmitted light they captured silhouette images of whole kernels in 'plain' (top) view and determined spatial size and shape parameters and Fourier descriptors. No misclassifications were found for CWRS and Canada Amber Durum wheat (CADW) while there was considerable overlapping between HRW and SWS wheats. Misclassifications among various cultivars of a single wheat class were greater. The authors suggested that features of anatomical parts of the kernels, such as size and shape of germ area, cheek and brush shape, and depth and width of crease may be essential for varietal identification.

Sapirstein et al. (1987) extended the study of Neuman et al. (1987) for classifying CWRS wheat, barley, rye, and oats. All cereal grain classes were disjoint with oats and wheat being well separated. For a sample size of 580 grains the classification error was 1%. The most promising results for objective determination of other cereal grains in wheat were reported by Sapirstein and Bushuk (1989). For a sample size of more than 1000 kernels, 98.4% of CWRS wheat were correctly classified using a linear discriminant function and assuming Gaussian patterns. The classification accuracies reported in their study for CWRS wheat, barley, oats, and rye were 98.4, 93.7, 78.3, and 98.0%, respectively. A substantial improvement in cereal grain discrimination was achieved when the morphology based discriminant model was supplemented with mean kernel reflectance. The classification accuracies for wheat, barley, oats, and rye using reflectance and morphological features were 99.2, 95.7, 95.3, and 98.3%, respectively.

Discriminating foreign material from wheat was first attempted by Zayas et al. (1989). Multivariate discriminant analysis was used to distinguish between wheat and not wheat and among weed seeds. They developed a structural prototype to distinguish between wheat and non wheat. The structural prototype method discriminated well between wheat and non wheat and many times it failed to identify stones present in the sample. It is worth mentioning that they described the difference between dockage and foreign material and suggested about the inclusion of other non-grain material in the grain classifier.

Zayas et al. (1990) studied special problems associated with applying MVS to the grain industry. They attempted to discriminate the whole corn kernels from the broken kernels. They evaluated the effect of image resolution on the discrimination by conducting experiments with different optical settings. Though their study had a drawback of manual placement of the sample with fixed orientation, they could correctly classify all of the broken kernels and 98% of the whole kernels.

Symons and Fulcher (1988a, 1988b) investigated the potential of the techniques of Neuman et al. (1987) to discriminate Eastern Canadian wheat classes and varieties. They used shape and size features derived from backlit images. For a sample size of 225 kernels, they found that 94% of Soft White Winter (SWW) wheat were correctly classified using a 4 way classification among SWW, HRW, hard red spring originated from Europe (HRS_E), and hard red spring wheat originated from Western Canada (HRS_W). Sixteen percent of HRS_W were confused as HRW. The HRS_W sample was comprised of cultivars 'Katepwa' and 'Columbus'. These cultivars were also included in the study by Neuman et al. (1987). It can be mentioned again that Neuman et al. (1987) found no confusion between CWRS and CWRW wheat classes. Such contrasts in results suggest that there is a need for large database to develop a robust classifier.

The inadequacy of the plan-form size and shape features for discriminating among different cultivars of a wheat class was also experienced by Symons and Fulcher (1988a). For three of the wheat cultivars of SWW, correct classifications of less than 60% were reported. In a subsequent study, Symons and Fulcher (1988b) used additional features derived from the bran layer and crease from the image of transverse section of kernels to aid in classification among different cultivars of SWW class. Classification results were unsatisfactory with errors of more than 50%.

The first four Fourier descriptor magnitudes were used for discriminating Australian wheat varieties by Myers and Edsall (1989). They also used additional features derived from side view of the kernels to improve the classification. Their study suggested that open curve Fourier components were useful parameters for Australian wheat variety discrimination. Errors up to 22% were reported in their study.

A detailed study on Fourier descriptors for the discrimination of Australian wheat varieties was carried out by Barker et al. (1992c). They used both dimensionless and absolute Fourier descriptors. They suggested that the absolute Fourier set clearly outperformed the dimensionless feature set and also that Fourier descriptors alone were not enough for a practical classification system.

Barker et al. (1992a, 1992b, 1992d) used features derived from contour of a wheat kernel positioned in a fixed orientation to discriminate among Australian wheat varieties. Overall correct classification among eight varieties was less than 65%. They used ray parameters (i.e., radial distance from the centroid), slice and aspect ratio parameters, and Chebychev coefficients features in their study.

Features only based on size and shape are not satisfactory to build a grain classifier. Therefore, researchers started investigating the potential of colour features for grain classification. Neuman et al. (1989a, 1989b) examined colour attributes of individual kernels of 6 Canadian wheat classes represented by 10 varieties. They achieved 88% correct varietal classification for pair-wise discrimination using mean red, blue, and green reflectance features of the pixels. The correct classification of individual varieties varied from 34 to 90%. Average correct classifications for the SWS, AD, and HRS classes of wheat were 76.76, and 62%, respectively. Poor classifications of 56% and 34% were achieved for CPS wheat classes.

The vitreosity of durum wheat was studied by Sapirstein and Bushuk (1989) using images of transilluminated kernels and specifying the frequency distribution of grey levels. They found 95% correlation between vitreosity computed by image analysis and replicated official inspection of hard vitreous kernels.

3.2.3 Research towards Special Needs

Researchers (Jayas and Bulley, Personal Communication) evaluated the potential of applying machine vision techniques to the grain industry. But found that before building a machine vision based grain classifier, the special problems like touching kernels, dockage identification, testing the classifier with samples which are not included in the training, testing the classifier with samples from various growing regions, an implementable sample presentation method to the FOV of the camera need further investigation. Moreover, 100% classification has to be achieved to build a robust classifier because of the tight tolerances in grade determinants (Appendix A). The grains have to be identified in bulk samples to automate the unloading of grains from the railcars at the receiving end of the terminal elevators. Grain quality needs to be monitored for shipped grain on a continuous basis. Research to solve some of these special problems has been the main focus of the research in the Department of Biosystems Engineering.

Shatadal et al. (1995a, 1995b) developed a software to separate the touching kernels. The algorithm was successful in disconnecting 95% of HRS wheat and durum wheat, 94% barley, 89% rye, and 79% oats conjoint kernel regions.

Majumdar et al. (1996b) used textural features for cereal grain classification. They achieved 95.7, 96.9, 97.8, and 97.9% classification accuracies for CWRS wheat, durum wheat, barley, and rye, respectively with textural features extracted from red colour band. The classification of HRS wheat was improved to 100% when textural features from '(3R+2G+B)/6' colour band were used.

Shashidhar et al. (1996) extracted basic morphological features from the images of touching kernels by an ellipse fitting algorithm. Limited testing was done on the algorithm to evaluate its ability to count objects in an image and to estimate basic morphological features of individual kernels separated by the algorithm. They reported that most of the estimated size features using the algorithm were not significantly different from the measured parameters obtained ($p>0.05$) by digital image processing.

Most of the researchers used clean and pedigreed samples for classification of cereal grains, and of different classes and varieties of wheats. Some researchers placed the grains manually in a specific orientation which defeats the main purpose of automation. In many cases, the sample size was small and an overall classification accuracy of about 96% was achieved using morphological and reflectance features for classification of cereal grains. Researchers focussed their research on finding solutions for the special problems and needs. Testing the classification accuracies with big sample size, solving the problem of touching kernels, and identifying non-grain material are the some of the special problems.

CHAPTER:4 DOCKAGE IN WHEAT

4.1 Definition

Dockage is the material that is separable from the grain sample by the use of an approved cleaning equipment in order that the grain can be assigned the highest grade for which it qualifies. Dockage is reported in percentage by mass. The percentage of dockage in a sample is reported in increments of 0.5% when the grain is not commercially clean and in the export shipments to the nearest 0.1% (when authorized by the Canadian Grain Commission to contain dockage).

4.2 Determination of Dockage in Samples

Dockage is assessed by running the uncleaned representative sample of 500 or 1000 g through the Carter Dockage Tester. A schematic diagram of the Carter dockage tester is shown in Fig. 4.1. For CWRS wheat, No. 25 riddle, No. 6 buckwheat sieve (a triangular hole sieve with 2.38 mm inscribed circle), and two No. 25 buckwheat sieves (a triangular hole sieve with 1.98 mm inscribed circle) are used in the Carter dockage tester. The feed control of the dockage tester is set at #6 position and the air control is set at minimum of #4 and can be varied based on the material over the riddle. In the dockage tester, dockage fractions are collected in pans numbered 1, 2, 5, and 6. The collected fractions are reported in percentage by mass.

The dockage fraction collected over the riddle (from pan 2, Fig. 4.1) contains wheat heads, large seeds (like wildoats, barley, oats, soybean), and other non-grain material (like

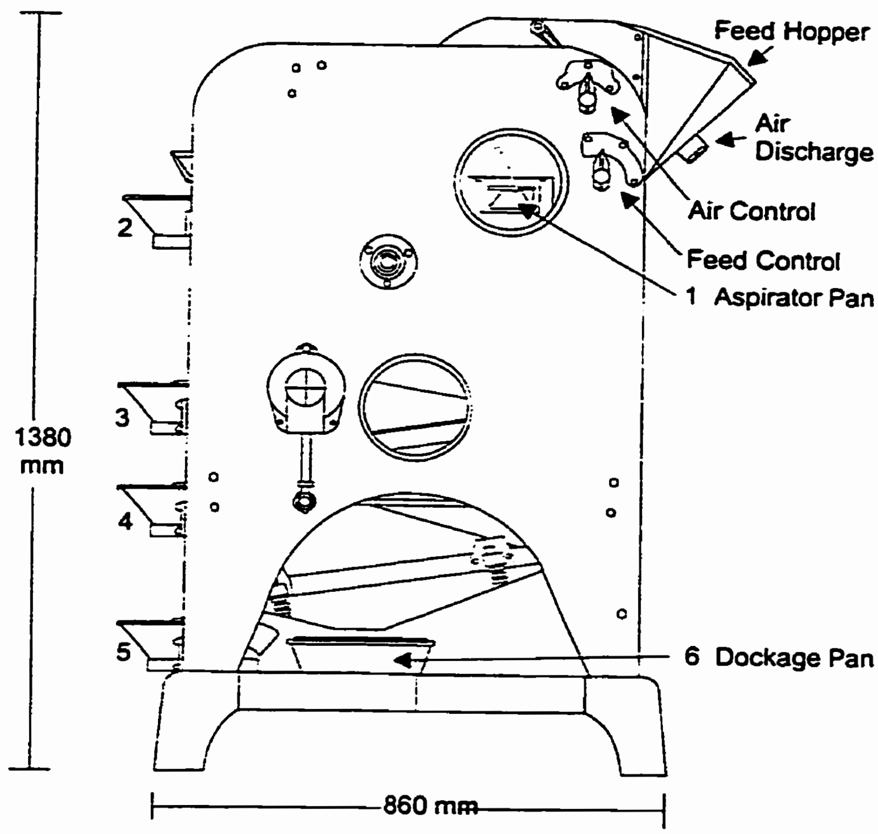


Fig. 4.1 Schematic diagram of the Carter dockage tester.

stones, cut stem pieces etc.). The wheat grain is collected in pans 3 and 4 of the Carter dockage tester. In pan 5, small seeds like flax, wild buckwheat, and broken wheat pieces are collected. In pan 6, heavily broken wheat grains, dust, and small seeds like canola and mustard are collected. Chaff, dust, and cut stem pieces are collected in pan 1.

4.3 Composition of Dockage

As defined in the Grain Grading Handbook for Western Canada, the following are the dockage constituents (Anonymous 1994):

(i) foreign material removed over the riddle, less any portion which is eligible for machine separation (pan 2),

(ii) material removed by aspiration (pan 1),

(iii) material removed by No. 5 buckwheat sieve in the lower position (pan 5 and 6),

(iv) a maximum of 10.0 % by mass of soft earth pellets hand picked from the cleaned sample, and

(v) any material removed by cleaning for grade improvement.

4.4 Dockage Vs Foreign Material

Foreign material is defined as the material other than the grain of the same class, which remains in the sample after the removal of dockage. Based on the separation of the impurities by the dockage tester, they are referred to either dockage or the foreign material. In wheat, other cereal grains like barley, rye, oats, etc. and non-grain material like earth pellets, chaff, fertilizer pellets are termed as foreign material if collected on pans 3 and 4 with wheat and are termed as dockage if they get separated by the dockage tester.

Some of the dockage constituents (soybean, earth pellets, stones, and wild mustard) are not included in the dockage class as they are very rare constituents. Wheatheads, chaff, wildoats, flax, wild buckwheat, canola, and broken kernels are identified as dockage constituents. The dockage constituents are shown in Appendix D. The main dockage constituents and other cereal grains (durum wheat, barley, rye, and oats) were used in this study to assess the capability of the morphological features for their identification.

CHAPTER 5: METHODS AND MATERIALS

5.1 Vision Hardware

The hardware of the image acquisition system used in this study consisted of a 3-chip CCD (couple charge device) colour camera (Model DXC-3000A, SONY) with a zoom lens (VCL-1012BY) of 10-120 mm focal length, a camera control unit (CCU) (Model CCU-M3, SONY), a diffuse illumination chamber, a colour monitor (Model PVM-1342Q, SONY), a colour frame grabber (Model DT 2871, Data Translation Inc., Marlboro, MA), a frame processor (Model DT 2858, Data Translation Inc., Marlboro, MA), a personal computer (PC) (Model 80386, UNISYS) with 8Mb of RAM and 80Mb hard disk, a SUN SPARC station II with 32Mb RAM and 400Mb hard disk, and an optical disk drive (Model SMC-S501, SONY).

The camera was mounted on a stand (Model m3, Bencher Inc., Chicago, IL) which provided easy vertical movement. The camera was controlled by the camera control unit which enabled selectable manual or automatic iris, video signal gain control, and white-black balance of the camera. The frame grabber and the frame processor boards were installed in the PC. An aurora subroutine library (Aurora, Data Translation Inc., Marlboro, MA) was installed in the PC to support the frame grabber and the frame processor. The PC was networked to the SUN SPARC station and the optical disk drive. The colour monitor was used for on-line image display.

The camera captured images from the samples placed in the illumination chamber.

The camera outputted three parallel analog video signals, namely red (R), green (G), and blue (B), corresponding to the three NTSC (National Television System Committee) colour primaries, and a sync signal. The camera control unit performed the time-division multiplexing and dc restorations of the RGB signals, and time signal generation for the frame grabber. The frame grabber digitized the RGB analog video signals to three 8-bit 512 x 512 size RGB digital images, at a speed of 30 frames per second, and stored them in three of the four on-board buffers. The acquired digital images were then transferred to the optical disk for storage.

5.2 Sample Illumination

Uniform diffused lighting was used in all the experiments. The illumination chamber consisted of a sample placement platform, a semi-spherical steel bowl of approximately 0.39 m in diameter, painted white and smoked with magnesium oxide on its inner side with an opening of 0.125 m in diameter at its top (through which the samples were viewed by the camera). A circular fluorescent tube (305 mm in diameter, 32 W, Model FC1279/CW, Philips, Singapore) was placed around and just below the surface level of the sample placement platform of the light chamber. The semi-spherical steel bowl was used as a diffuser. A voltage regulator (Model CVS, Sola Canada Inc., Toronto, ON) controlled the voltage to the lamp within ±0.5V. A variac was used to maintain a constant voltage (120±0.1 V) to the light source. A light controller (Model FX0648-2/120, Mercron, Richardson, TX) was used with the fluorescent lamp. The photo diode light sensor of the light controller automatically detected the illumination level in the light chamber and adjusted the AC frequency of the lamp to maintain a stable level of illumination. The frequency of the AC power output varied between 140 kHz at the minimum light level to 60 kHz at full power.

5.3 Illumination Standardization

A Kodak white card with 90% reflectance (E 152-7795, Eastmen Kodak Co., Rochester, NY) was used as a white reference to standardize the illumination level. The lamp voltage was set to the rated value of 120 V. An image of the white card was acquired over a small central area of 50 x 50 pixels and the mean grey level values of R, G, and B bands were computed and used as illumination level indicators. By manually adjusting the iris control and performing the white balance with the CCU, all three values were adjusted to 250±1.

5.4 Grain and Dockage Samples

Composite grain samples of (HRS) wheat (grade 1, 2, and 3), durum wheat (grade 1, 2, 3, and 4), barley (grade 1, and EX1), oats (grade 1, and 3), and rye (grade 1) were collected from different growing regions of Western Canada for the 1994 growing season by the Industry Services Division of the Canadian Grain Commission, Winnipeg, MB. Samples of seven grain types (CWRS-1, CWRS-2, CWRS-3 wheat, durum wheat, barley, rye, and oats) were selected from 20 growing regions. These regions were chosen using the climatic subdivisions of the Canadian Prairies (Putnam and Putnam, 1970). Three hundred kernels (25 kernels in an image frame) from each growing region were used for each grain type and grains from five randomly selected growing regions were analyzed.

Dockage samples were obtained by running 15 kg of uncleaned farm samples of CWRS wheat from Glenlea Research Farm through the Carter dockage tester. One hundred grams of each dockage tester fractions were collected from the Industry Services Division of Canadian Grain Commission, Winnipeg, MB.

5.5 Sampling Technique

For overall sampling, each composite grain sample (1000-1500g) was poured into a large plastic container and mixed thoroughly. A scoop was used to take grains randomly from different regions of the container to give a subsample of 75 g. Before withdrawing the second subsample, the remaining grains in the plastic container were re-mixed. In this way three subsamples were collected. The three subsamples were remixed to give a sample. The sample was mixed thoroughly by passing it through the Boerner Divider for 4 times. For image acquisition of individual kernels, 300 kernels were randomly picked from the sample for testing.

For each dockage class, 1500 individual objects were randomly picked from the fractions (from Glenlea Research Farm Samples) collected from the dockage tester and from the fractions obtained from the Industry Services Division of Canadian Grain Commission, Winnipeg, MB.

5.6 Image Acquisition

The system was stabilized for 30 min. The illumination standardization and white balancing was done and repeated after every three images. White background was used for samples of canola, wild buckwheat, wildoats, and flax for better thresholding. In each frame 25 objects were placed, imaged and stored as digital images on the optical disk for further analysis.

CHAPTER 6: IMAGE ANALYSIS

6.1 Thresholding

Thresholding is a process which converts a multi grey level image to a binary image so that objects can be distinguished from the background. Thresholding can be done either manually or automatically. In manual thresholding, a threshold value is specified by the user and the pixels whose grey levels are less than the threshold value are set to background (0) and the remaining pixels are set to object (1). Manual thresholding is time consuming as the thresholded image has to be displayed for every threshold value specified by the user to visually examine the thresholded image and to decide the final threshold value.

In automated thresholding (Parker 1994), an algorithm is used which decides the threshold value by itself. For this study, the automated thresholding was used. The threshold value was calculated by the principle of iterative selection in the developed algorithm. It provided an estimate of the average grey level of both the background (Tb) and the objects (To) and used the average of these two levels [$T = \frac{1}{2}(Tb+To)$] as the threshold value T. The red band was used for thresholding the image. The mean grey level of the red band [(255+0)/2] was used to initialize the iterative procedure. The values of To and Tb were adjusted by calculating the mean grey levels of pixels whose grey levels were more than or less than the initialized T value. A new threshold value was calculated by using the adjusted Tb and To. The process was repeated until the same threshold value T was produced on the two consecutive iterations. The maximum number of iterations was preset to 40 to reduce the run time of the algorithm.

6.2 Region Labelling

Region labelling was used to assign a unique label or an identifier to each object in the binary image. The region labelling algorithm scanned the binary image once from the top left to the bottom right. The first encountered unlabelled object pixel was assigned a unique label. Then from that pixel the region was expanded and the same label value was propagated by following 8-neighbours connectivity. The propagation of same label value continued until no more neighbouring pixels of objects could be found. The scanning of the binary image was resumed and the same process was continued until all the objects were labelled with their unique label. After labelling there could be some pixels in the object region with the background grey level value (called 'hole') or some pixels in the background with the object grey levels (called 'extra-region'). It is very important to change the values of these pixels to the right values for the accurate measurement of the morphological features. Therefore, a holefilling and region-deleting-subroutine was used to solve this problem. Starting from a background pixel, the whole background region was connected by following the 8-neighbours connectivity. The left out pixels whose grey levels were that of the background were changed to the respective object label value. Any region which had 30 or less number of pixels was deleted.

6.3 Feature Extraction

From each object, morphological and basic color features were extracted. This section describes all these features and their calculations.

6.3.1 Spatial Calibration

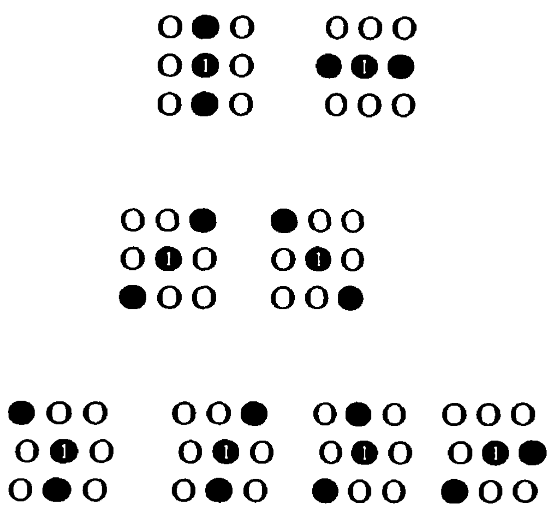
In a digital image, all the morphological features were calculated in pixel units. A scaling factor was determined by taking an image of a Canadian quarter whose diameter was known. This scaling factor was used in expressing the features in real world dimensions. The rectangular pixel quarter image was converted into square pixel image and its length and width were calculated in pixel units. The mm/pixel was calculated as

mm/pixel = (2 x coin diameter) / (length+width).

6.3.2 Size Features

6.3.2.1 Area The area of an object was calculated by counting the number of pixels contained in the object. The area was expressed in mm^2 by multiplying the total number of pixels by the scaling factor obtained from the coin image twice (both for x and y axis scaling).

6.3.2.2 Perimeter The perimeter was calculated by adding the distances between all the successive pairs of pixels in the boundary of the object. Generally the perimeter of a region is calculated by adding the number of pixels on the boundary. But a pixel represents an area not a linear distance. All the boundary pixels were matched with the templates shown in Fig. 6.1, and the distance represented by each pixel was weighted as 1 if all neighbours were horizontal or vertical, or weighted as 1.414 if all neighbours were diagonal, or weighted as 1.207 if there was one diagonal and one non-diagonal pixel. The perimeter was expressed in mm by multiplying total pixel distance on the boundary by the scaling factor obtained from the coin image.



Templates for pixel distance 1.

Templates for pixel distance 1.414

Templates for pixel distance 1.207

Fig. 6.1 Distance templates for boundary pixels

6.3.2.3 Centre of Mass Centre of mass was not used as a feature but was calculated for extracting other features like principal axis length, Fourier descriptors etc. The centre of mass of an object of N pixels was calculated by the following equations (Baxes, 1994).

$$\bar{x} = \frac{1}{N}\sum_{i=0}^{N-1} x_i \qquad (6.1)$$

$$\bar{y} = \frac{1}{N}\sum_{i=0}^{N-1} y_i \qquad (6.2)$$

where, N = total number of pixels in an object

x_i ,y_i = x, y coordinate of the i^{th} pixel

6.3.2.3 Length of Principal Axis Principal axis, also known as the major axis, is defined as the longest line that can be drawn through the centroid of the object. The candidate pixels were identified by finding the distance between each possible pair of boundary pixels which could be connected by a straight line and the distance was taken as the length of principal axis. The length of principal axis was expressed in mm by multiplying the length in pixel units by the scaling factor.

6.3.2.4 Length of Minor Axis The minor axis is defined as the longest line that can be drawn perpendicular to the principal axis through the centroid. The candidate pixels on the boundary were identified and the distance between the pixels was calculated as the width of minor axis.

6.3.2.5 Length and Width of Bounding Rectangle The length and width of bounding rectangle were calculated by finding the rectangular box that would entirely surround the object.

6.3.2.6 Minimum, Maximum, Standard Deviation of Radii The distance of each pixel on the boundary from the centroid was calculated and the minimum, maximum, and standard deviation of the distances were reported as minimum, maximum, and standard deviation of radii.

6.3.3 Shape Features

All of the following shape features were derived from the size features:

$$Thinnes\ Ratio = \frac{Perimeter^2}{Area} \tag{6.3}$$

$$Rectangular\ Aspect\ Ratio = \frac{Length\ of\ bounding\ rectangle}{Width\ of\ bounding\ rectangle} \tag{6.4}$$

$$Aspect\ Ratio = \frac{Length\ of\ Principal\ Axis}{Length\ of\ Minor\ Axis} \tag{6.5}$$

$$Area\ Ratio = \frac{Length\ x\ Width}{Area} \tag{6.6}$$

$$\textit{Radius Ratio} = \frac{\textit{Maximum Radius}}{\textit{Minimum Radius}} \tag{6.7}$$

$$\textit{Haralick Ratio} = \frac{\textit{Mean of Radii}}{\textit{Standard Deviation of Radii}} \tag{6.8}$$

6.3.4 Boundary Descriptors

6.3.4.1 Fourier Descriptors The discrete Fourier transform (DFT) can be used as the basis for describing the shape of a boundary on a quantitative basis. Consider an object with N pixels on the boundary in the xy plane. The coordinates of these pixels can be expressed in the form of x(k) = x_K and y(k) = y_K and with this notation the entire boundary of the image can be represented as the sequence of coordinates as:

f(k) = [x(k), y(k)] for k = 0, 1, ...N-1. Each coordinate pair is treated as a complex number so that

$$f(k) = x(k)+jy(k) \quad \text{for } k=0,1,....N-1. \tag{6.9}$$

The discrete Fourier transform of f(k) is:

$$a(u) = \frac{1}{N}\sum_{k=0}^{N-1} f(k)\exp[-j2\pi uk/N] \tag{6.10}$$

for u = 0, 1, 2, ...(N-1).

where, N = total number of pixels on the boundary

The complex coefficient a(u)'s are the called Fourier descriptors. The boundary f(k) can be restored by taking inverse Fourier transform of a(u):

$$f(k) = \frac{1}{N}\sum_{u=0}^{N-1} a(u)\exp[j2\pi uk/N] \qquad (6.11)$$

for k = 0, 1, 2, ...(N-1).

The Fourier descriptor magnitudes were calculated by the following equation.

$$FDM=\sqrt{R(u)^2+I(u)^2} \qquad (6.12)$$

where R(u), and I(u) are given by:

$$R(u) = \frac{1}{N}\sum_{u=0}^{N-1} d\cos[2\pi uk/N] \qquad (6.13)$$

$$I(u) = \frac{1}{N}\sum_{u=0}^{N-1} d\sin[2\pi uk/N] \qquad (6.14)$$

And 'd' is the distance of a particular pixel from the centroid of the object.

6.3.4.2 Moments

The spatial moments of an object give statistical measures related to an object's characterization.

The *zero-order* spatial moment is computed as the sum of the brightness values in an object. In the case of a binary image, this is simply the number of pixels in the object, because every pixel in the object is equal to 1 (object =1). Thus the zero-order spatial moment of a binary object is its area.

The *first-order* spatial moments of an object contain two independent components namely *x* and *y*. They are the grey level weighted sums of x and y coordinate locations of each pixel in the image. In the case of a binary image, the first-order x spatial moment is just the sum of the x coordinates of all the pixels of the object because the object pixels are equal to 1. The first-order spatial moments of an object represent the object's energy and how it is spatially distributed.

The moment of order (p+q) for a digital image is defined as:

$$m_{pq} = \sum_{i} \sum_{j} i^{p} j^{q} F(i,j) \qquad (6.15)$$

for p, q = 0, 1, 2, ..., ℓ where:

ℓ = user-selected value to calculate a specific order of moment, and

F(i, j) = gray level value at coordinate (i, j).

F(i, j) is 1 for any binary image.

The above equation uses the image origin rather than the object's origin (centroid). The features used should be invariant to translation, orientation, and scaling. Because the general moments are position dependent, central moments are calculated as:

$$\mu_{pq} = \sum_i \sum_j (i - c_i)^p (j - c_j)^q \tag{6.16}$$

for p, q = 0, 1, 2, ..., k where:

k = user-selected value to calculate a specific order of central moment,

c_i = m_{10} / m_{00},

c_j = m_{01} / m_{00}, and

(c_i, c_j) = the centre of gravity of the kernel.

The normalized central moments, η_{pq}, were calculated from the central moment, μ_{pq}:

$$\eta_{pq} = \mu_{pq} / \mu_{00}^{r} \tag{6.17}$$

where,

r = $\frac{1}{2}(p + q) + 1$.

The following set of four moments which are invariant to translation, rotation, and scaling were used as the moment features.

$$M_1 = \eta_{20} + \eta_{02} \tag{6.18}$$

$$M_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2 \tag{6.19}$$

$$M_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \tag{6.20}$$

$$M_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \tag{6.21}$$

6.4 Basic Colour Features

The commonly used colour models for image processing are the RGB (Red, Green. and Blue), YIQ (Luminance, Imphase, and Quadrature), and HSI (Hue, Saturation. and Intensity). The most often used, hardware oriented, RGB colour model was used in this study. In the RGB colour model, each colour appears in its primary spectral components of red, green, and blue. The Cartesian coordinate based colour model is shown in Fig. 6.2.

In the RGB colour model, the R, G, and B values are at three corners and cyan. magenta, and yellow are at other three corners. The RGB color model is additive color system and the CMY color model is subtractive color system. The grey scale is represented by the dotted line from black to white. In the images with RGB colour model, each pixel contains a coordinate position (x, y), and three basic R, G, and B colour values associated with it. The mean of R, G, and B, and standard deviation of these three components were calculated and used as the basic colour features. The average intensity of the object region was calculated using the mean of R, G, and B values as:

$$I = (R+G+B)/3 \tag{6.22}$$

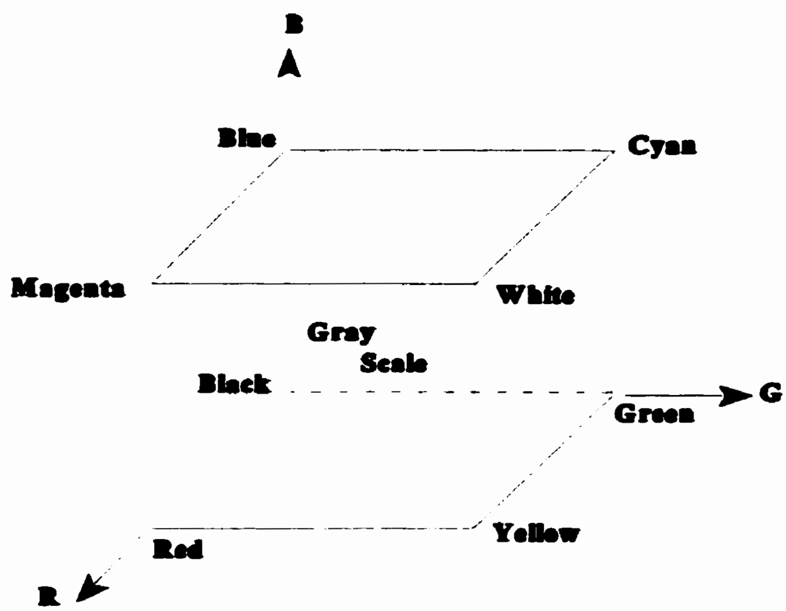


Fig. 6.2 RGB Colour Model

The other most often used colour model is the HSI which can be derived from the RGB model. A detailed description about the other colour models and their uses can be found in Gonzalez and Woods (1992).

6.5 Object classification

There are two different ways of classifying objects. One way is to find relations among the objects with the purpose of grouping them. For example, the similarities among grains which are used to group them into different classes, like cereal grains, oilseeds, speciality crops, etc. Statistical methods covering this kind of classification are called clustering, and the general principle is to group the observation vectors into clusters of a certain similarity. The second way of classification is to assign objects into defined groups. The statistical method for this classification is called discriminant analysis, and this is the usual kind of classification which follows image analysis for recognition purposes.

The task of discriminant analysis is to find a decision rule which assigns an object described by a number of m features to one of several groups P_i ($i = 1, 2, ..., n$) in a population. The simplest case is discrimination by one feature (e.g., object area) and two groups. If we know the probability density function of this feature for each group, say $f_1(x)$ and $f_2(x)$, the object should be assigned to the group with the higher probability density, i.e., assigned to group P_1 if $f_1(x) > f_2(x)$. This is called likelihood ratio method.

This method may be improved if we know that a proportion π_1 of the total population belongs to P_1 and the remaining π_2 belongs to P_2. In this case, the object is assigned to P_1 if $\pi_1 f_1(x) > \pi_2 f_2(x)$ which is the Bayesian classifier.

If we assume that x is normally distributed in each group as $N(\mu_i, \sigma_i^2)$ then:

$$f_i(x) = \frac{1}{\sqrt{2\pi\sigma_i}} \exp\left[-\frac{(x-\mu_i)^2}{2\sigma_i^2}\right] \tag{6.23}$$

and further if $\sigma_1 = \sigma_2 = \sigma$ for the two groups then:

$$f_1(x)/f_2(x) = \exp\left[-\frac{(x-\mu_1)^2-(x-\mu_2)^2}{2\sigma^2}\right] \tag{6.24}$$

Setting this expression equal to 1 (or π_1 / π_2) gives the threshold for group separation.

The corresponding expression for a multivariate normal distribution of feature vectors $\mathbf{x}_i$ with dispersion matrices $\boldsymbol{\Sigma}_1 = \boldsymbol{\Sigma}_2 = \boldsymbol{\Sigma}$ is:

$$f_1(x)/f_2(x) = \exp[(\mu_1-\mu_2)'\Sigma^{-1}x - \frac{1}{2}(\mu_1-\mu_2)'\Sigma^{-1}(\mu_1+\mu_2)] \tag{6.25}$$

In the univariate case, a threshold is used for separation of groups, in the bivariate case a line, and in the multivariate case it is the hyperplanes which separate groups in the multi-dimensional feature space. The hyperplane for separating two groups is defined by setting the discriminant functions equal to $\log(\pi_2 / \pi_1)$:

$$(\mu_1-\mu_2)'\Sigma^{-1}x - \frac{1}{2}(\mu_1-\mu_2)'\Sigma^{-1}(\mu_1+\mu_2) = \log(\pi_2/\pi_1) \tag{6.26}$$

In general, the distribution of the features is not known. One approach to estimating the error rate of a classifier is to compute it from the assumed parametric model. However, there are many problems with this approach: (i) estimate is almost always overoptimistic. (ii) characteristics that make the design samples peculiar or unrepresentative are not revealed, and (iii) in more general situations it is very difficult to compute the error rate exactly, even if the probabilistic structure is completely known (Duda and Hart 1973).

An empirical approach that avoids these problems is to test the classifier experimentally. For discrimination, three special cases are considered of practical importance:

The Resubstitution Method — The parameters of the discriminant functions are estimated from the same population which is classified into groups. The number of incorrectly classified observations m_i of the n_i observations in group P_i define the error rate as $e_i = m_i / n_i$, and $e = \pi_1 e_1 + \pi_2 e_2$ for two groups.

The Cross-validation Method — This method (also known as *leaving-one-out* method) estimates the discriminant functions from the sample data minus one (n-1) observations. The omitted observation is then classified as the unknown observation and this procedure is repeated until all observations (n) are classified. The corresponding error rate is $e_i = b_i / n_i$, and $e = \pi_1 e_1 + \pi_2 e_2$ (for two groups) where b_i is the number of misclassified observations in group P_i.

The Hold Out Method — This method uses a separate population (training data) for construction of the discriminant functions, and another population for testing the classification results. If the observations are normally distributed, the error rate may be estimated by calculating the area of the region where the density function is overlapped by a density function from another group. For the two group problem, the region is estimated by $R_1 = \{\mathbf{x}: f_1(\mathbf{x} \mid \boldsymbol{\theta}_1) / f_2(\mathbf{x} \mid \boldsymbol{\theta}_2) > \pi_2 / \pi_1\}$ where $\boldsymbol{\theta}_i$ are the estimated parameters of the probability density function. The misclassification for group 1 is:

$$e_1 = \int_{R_2} f_1(\mathbf{x} \mid \theta_1)\, d\mathbf{x} \tag{6.27}$$

where,

R_2 = feature space for group 2.

The separation of groups in the feature space depends on how well the parameters of the distribution functions are estimated. For example, if no errors are made on 50 test samples, with probability 0.95, the true error rate is between 0 - 8%. The classifier would have to make no errors on more than 250 test samples to be reasonably sure that the true error rate is below 2% (Duda and Hart 1973).

The need for data to design the classifier and additional data to evaluate it presents the designer with a dilemma. If one reserves most of the data for the design, s/he cannot have confidence in the test. If one reserves most of the data for the test, s/he will not obtain a good design. The question of how best to partition a set of samples into a training set and a test set has received some analysis, and considerable discussion, but has no definitive answer (Duda and Hart 1973).

In fact, there are more options available than just partitioning the data, designing the classifier once, and testing it. For example, one might repeat this process several times, using a different partition each time, and average the resulting error-rate estimates. If computation costs are of no concern, one can use the cross-validation method. The basic advantage of this approach is that virtually all of the samples are used in each design, which should lead to a good design, and all of the samples are ultimately used in the tests. This procedure is particularly attractive when the number of available samples is quite small. When the number of samples is very large it is probably sufficient to partition the data into a single training set and a single test set (hold out method). Although there is no theory to guide the designer in intermediate situations.

6.5.1 Statistical Classifier For a set of observations containing one or more quantitative variables and a classification variable defining groups of observations, PROC DISCRIM of SAS (1990) develops a discriminant criterion to classify each observation into one of the groups. The derived discriminant criterion from this data set can be applied to a second data set during the same execution of DISCRIM. The data set that DISCRIM uses to derive the discriminant criterion is called the *training* or *calibration data set*.

When the distribution within each group is assumed to be multivariate normal, a parametric method can be used to develop a discriminant function. The discriminant function, also known as a *classification criterion*, is determined by a measure of generalized squared distance (Rao 1973). The classification criterion can be based on either the individual within-group covariance matrices (yielding a quadratic function) or the pooled covariance matrix (yielding a linear function); it also takes into account the prior probabilities of the groups. The calibration information can be stored in a special SAS data set and applied to other data sets.

When no assumptions can be made about the distribution within each group, or when the distribution is assumed to be different from multivariate normal distribution, non-parametric methods can be used to estimate the group-specific densities. These methods include the *kernel method* and *k-nearest neighbor methods* (Rosenblatt 1956; Parzen 1962).

Either Mahalanobis distance or Euclidean distance can be used to determine proximity. Mahalanobis distance can be based on either the full covariance matrix or the diagonal matrix of variances. In the *k-nearest neighbor* method, the pooled covariance matrix is used to calculate the Mahalanobis distances. In the kernel method, either the individual within-group covariance matrices or the pooled covariance matrix is used to calculate the Mahalanobis distances.

The DISCRIM procedure can produce an output data set containing various statistics such as means, standard deviations, and correlations. The DISCRIM evaluates the performance of a discriminant criterion by estimating *error rates* (probabilities of misclassification) in the classification of future observations. When the input data set is an ordinary SAS data set, the error rate can also be estimated by cross-validation.

Bayes' Theorem — Assuming that the probabilities of group membership are known and the group-specific densities at **x** can be estimated, DISCRIM computes p(t | **x**), the probability of **x** belonging to group t, by applying Bayes' theorem:

$$p(t|\mathbf{x}) = q_t f_t(\mathbf{x})/f(\mathbf{x}) \tag{6.28}$$

where,

$p(t \mid \mathbf{x})$ = posterior probability of an observation **x** belonging to group t,

q_t = prior probability of membership in group t,

$f_t(\mathbf{x})$ = group-specific density estimate at **x** from group t, and

$f(\mathbf{x})$ = $\sum_t q_t f_t(\mathbf{x})$, estimated unconditional density at **x**.

The DISCRIM partitions a p-dimensional vector space into regions R_t, where the region R_t is the subspace containing all p-dimensional vectors **y** such that $p(t \mid \mathbf{y})$ is the largest among all groups. An observation is classified as coming from group t if it lies in region R_t.

Parametric methods — Assuming that each group has a multivariate normal distribution, the DISCRIM develops a discriminant function or classification criterion using a measure of generalized squared distance. The DISCRIM also computes the posterior probability of an observation belonging to each class. The squared distance from $\mathbf{x}$ to group t is:

$$d_t^2(\mathbf{x}) = (\mathbf{x} - \mathbf{m}_t)'\mathbf{V}_t^{-1}(\mathbf{x} - \mathbf{m}_t) \tag{6.29}$$

where,

$\mathbf{V}_t$ = $\mathbf{S}_t$, if the within-group covariance matrices are used,

$\mathbf{V}_t$ = $\mathbf{S}$, if the pooled co-variance matrix is used,

$\mathbf{x}$ = a p-dimensional vector containing the quantitative variables of an observation,

$\mathbf{m}_t$ = a p-dimensional vector containing variable means in group t,

$\mathbf{S}$ = pooled covariance matrix,

$\mathbf{S}_t$ = covariance matrix within group t, and

t = a subscript to distinguish the groups.

An observation is classified into group u, if setting t = u produces the largest value of $p(t \mid \mathbf{x})$. If this largest posterior probability is less than the threshold specified, $\mathbf{x}$ is classified into group '***other***'.

Non-parametric methods — Non-parametric discriminant methods are based on non-parametric estimates of group-specific probability densities. When the *k-nearest neighbor* method is used, the Mahalanobis distances are based on the pooled covariance matrix. The squared distance between two observation vectors, $\mathbf{x}$ and $\mathbf{y}$, in group t is given by:

$$d_t^2(\mathbf{x},\mathbf{y}) = (\mathbf{x} - \mathbf{y})'\mathbf{V}_t^{-1}(\mathbf{x} - \mathbf{y}) \tag{6.30}$$

where,

y = a p-dimensional vectors containing the quantitative variables of an observation.

The classification is based on the Bayes decision rule which classifies an entity (represented by its pattern vector, e.g., $\mathbf{x}$) to a class for which the entity has a maximum posterior probability (Hand 1981; Duda and Hart 1973). An observation $\mathbf{x}$ is classified into group u, if setting $t = u$ produces the largest value of $p(t \mid \mathbf{x})$. If there is a tie for the largest probability or this largest probability is less than the threshold specified, $\mathbf{x}$ is classified into group '***other***'.

Using the *k-nearest neighbor* rule, the k smallest distances are saved. Of these k distances, let k_t represent the number of distances that are associated with group t. Then the estimated group t density at $\mathbf{x}$ is:

$$f_t(\mathbf{x}) = \frac{k_t}{n_t v_k(\mathbf{x})} \tag{6.31}$$

where,

$v_k(\mathbf{x})$ = volume of the ellipsoid bounded by $\{\mathbf{z} \mid (\mathbf{z} - \mathbf{x})' \mathbf{V}^{-1} (\mathbf{z} - \mathbf{x}) = r_k^2(\mathbf{x})\}$,

$\mathbf{z}$ = a p-dimensional vector, and

n_t = number of training set observations in group t.

The nearest-neighbor method is equivalent to the uniform-kernel method with a location dependent radius $r_k(\mathbf{x})$. Since the pooled within-group covariance matrix is used to calculate the distances used in the nearest-neighbor method, the volume $v_k(\mathbf{x})$ is a constant, independent of group membership. When $k = 1$ is used in the nearest-neighbor rule, **x** is classified into the group associated with the **y** point that yields the smallest squared distance $d_t^2(\mathbf{x}, \mathbf{y})$.

The nearest-neighbor method is best used in applications where the choice of k is not critical (Silverman 1986, pp 98-99). A practical approach is to try several different values of k within the context of a particular application and to choose the one which gives the most satisfactory results.

6.6 Pattern Classification

After converting the rectangular pixel images into square pixel images, the images were thresholded using the automatic thresholding. Holes were filled and extra regions were deleted from the thresholded image. Morphological and basic colour features were extracted from the labelled and original images, respectively. The feature extraction algorithms were developed on an IBM compatible pentium 75 personal computer.

Discriminant analyses using PROC DISCRIM of SAS (1990) were carried out using cross-validation (leave-one-out), and hold-out methods. In each case, normal and non-pararmetric estimations were used. In the non-parametric estimation, k-nearest neighbour method was used with a k value of 5. In the hold-out method cereal grains from randomly selected 4 growing regions (300 kernels per growing region) were used as the training data set and from one growing region as the test data set. In the cross-validation method, the training data set used in the hold-out method was used for classification.

To determine the level of contribution by individual morphological features to classification, PROC STEPDISC (SAS 1990) was used. The training data set used in the hold-out method was used for feature selection in STEPDISC analysis. Individual rankings of features were determined using STEPDISC analysis by removing the best feature from the model and by re-ranking the remaining features i.e., for example in a model with five features the STEPDISC analysis was carried out with four features (the best feature from the five features model was removed) and the four features were ranked. This process was repeated with one feature in the final model.

CHAPTER 7: RESULTS AND DISCUSSIONS

7.1. Morphology-Colour Model Classifier

After some preliminary studies, the most discriminating 23 morphological features and 7 basic colour features were used for classification the dockage classes (wheathead, chaff, wildoats, canola, wild buckwheat, flax, and broken-wheat pieces) together with cereal grain classes (i.e., CWRS wheat, durum wheat, barley, rye, and oats).

When an independent data set was used for testing (the hold-out method) with normal estimation, the classification accuracies were: CWRS wheat (99.7), durum wheat (89.7), barley (95.3), rye (99.0), oats (99.7), wheathead (27.3), chaff (30.0), wildoats (99.3), canola (99.7), wild buckwheat (98.7), flax (99.3), and broken-wheat pieces (98.0%) [Table 7.1 (a)]. When hold-out method with non-parametric estimation was used the classification accuracies were: CWRS wheat (100.0), durum (97.3), barley (98.7), rye (99.3), oats (99.3), wheathead (2.3), chaff (12.0), wildoats (99.7), canola (100.0), wild buckwheat (100.0), flax (100.0), and broken-wheatpieces (100.0%)[Table 7.1(b)].

When the leave-one-out method with normal estimation was used, the classification accuracies were: CWRS wheat (99.2), durum wheat (96.6), barley (98.2), rye (96.3), oats (99.8), wheathead (96.3), chaff (92.6), wildoats (99.8), canola (99.4), wild buckwheat (98.5), flax (99.3), and broken-wheat pieces (97.6%)[Table 7.1(c)], and when non-parametric estimation was used the classification accuracies were: CWRS wheat (99.8), durum wheat (99.1), barley (98.3), rye (97.2), oats (99.9), wheathead (98.9), chaff (97.8), wildoats (99.8), canola (99.5), wild buckwheat (99.7), flax (99.8), and broken-wheat pieces

Table 7.1(a) Confusion matrix of the model with twelve classes for the hold-out method (Normal estimation)

Class (to)→ (from)↓	CWRS†	Durum‡	Barley	Rye	Oats	Whead¥	Chaff	Wildoats	Canola	wbwheat¤	Flax	Broken§
CWRS† (900)*	897 (99.7+)	0	0	3 (0.3)	0	0	3 (1.0)	0	0	0	0	0
Durum ‡ (300)	0	269 (89.7)	8 (2.7)	23 (7.7)	0	0	0	0	0	0	0	0
Barley (300)	0	11 (3.7)	286 (95.3)	3 (1.0)	0	0	0	0	0	0	0	0
Rye (300)	0	3 (1.0)	0	297 (99.0)	0	0	0	0	0	0	0	0
Oats (300)	0	0	0	1 (0.3)	299 (99.7)	0	0	0	0	0	0	0
Whead¥ (300)	0	0	0	0	200 (66.7)	82 (27.3)	18 (6.0)	0	0	0	0	0
Chaff (300)	0	0	0	61 (20.3)	140 (46.7)	6 (2.0)	90 (30.0)	0	0	0	0	0
Wildoats (300)	0	0	0	0	0	0	2 (0.7)	298 (99.3)	0	0	0	0
Canola (300)	0	0	0	0	0	0	0	0	299 (99.7)	0	0	1 (0.3)
Wbwheat¤ (300)	0	0	0	0	0	0	0	0	0	296 (98.7)	2 (0.7)	2 (0.7)
Flax (300)	0	0	0	0	0	0	0	0	0	0	298 (99.3)	2 (0.7)
Broken§ (300)	0	0	0	0	0	0	5 (1.7)	0	0	0	1 (0.3)	294 (98.0)

* Sample size, + Values expressed in percentage, † Canada Western Red Spring Wheat, ‡ Durum Wheat, ¥ wheathead, ¤ wild buckwheat, § broken-wheat pieces.

Table 7.1(b) Confusion matrix of the model with twelve classes for the hold-out method (Non-parametric estimation)

Class (to)→ (from)↓	CWRS†	Durum‡	Barley	Rye	Oats	Whead¥	Chaff	Wildoats	Canola	wbwheat¤	Flax	Broken§	Other
CWRS† (900)*	900 (100+)	0	0	0	0	0	0	0	0	0	0	0	0
Durum ‡ (300)	0	292 (97.3)	1 (0.3)	5 (1.7)	0	0	0	0	0	0	0	0	2 (0.7)
Barley (300)	0	3 (1.0)	296 (98.7)	0	0	0	0	0	0	0	0	0	1 (0.3)
Rye (300)	0	2 (0.7)	0	298 (99.3)	0	0	0	0	0	0	0	0	0
Oats (300)	0	0	0	0	298 (99.3)	0	0	0	0	0	0	0	2 (0.7)
Whead¥ (300)	1 (0.3)	1 (0.3)	7 (2.3)	1 (0.3)	277 (92.3)	7 (2.3)	0	0	0	0	0	0	6 (2.0)
Chaff (300)	2 (0.7)	0	1 (0.3)	0	234 (78.0)	0	36 (12.0)	0	0	0	0	1 (0.3)	26 (8.6)
Wildoats (300)	0	0	0	0	0	0	1 (0.3)	299 (99.7)	0	0	0	0	0
Canola (300)	0	0	0	0	0	0	0	0	300 (100)	0	0	0	0
Wbwheat¤ (300)	0	0	0	0	0	0	0	0	0	300 (100)	0	0	0
Flax (300)	0	0	0	0	0	0	0	0	0	0	300 (100)	0	0
Broken§ (300)	0	0	0	0	0	0	0	0	0	0	0	300 (100)	0

* Sample size, + Values expressed in percentage, † Canada Western Red Spring Wheat, ‡ Durum Wheat, ¥ wheathead, ¤ wild buckwheat, § broken-wheat pieces.

Table 7.1(c) Confusion matrix of the model with twelve classes for the leave-one-out method (Normal estimation)

Class (to)→ (from)↓	CWRS†	Durum‡	Barley	Rye	Oats	Whead¥	Chaff	Wildoats	Canola	wbwheat¤	Flax	Broken§
CWRS† (3600)*	3570 (99.2+)	0	0	0	0	0	0	0	0	0	0	0
Durum ‡ (1200)	0	1159 (96.6)	4 (0.3)	37 (3.1)	0	0	0	0	0	0	0	0
Barley (1200)	0	13 (1.1)	1178 (98.2)	9 (0.6)	0	0	0	0	0	0	0	0
Rye (1200)	0	36 (3.0)	8 (0.9)	1156 (96.3)	0	0	0	0	0	0	0	0
Oats (1200)	0	0	0	2 (0.2)	1198 (99.8)	0	0	0	0	0	0	0
Whead¥ (1200)	0	0	0	0	0	1156 (96.3)	44 (3.7)	0	0	0	0	0
Chaff (1200)	0	0	0	0	0	33 (2.8)	1111 (92.6)	0	0	0	0	56 (4.7)
Wildoats (1200)	0	0	0	0	0	0	3 (0.3)	1197 (99.8)	0	0	0	0
Canola (1200)	0	0	0	0	0	0	4 (0.3)	0	1193 (99.4)	2 (0.2)	0	1 (0.1)
Wbwheat¤ (1200)	0	0	0	0	0	0	0	0	8 (0.7)	1182 (98.5)	0	0
Flax (1200)	0	0	0	0	0	0	1 (0.1)	0	0	0	1192 (99.3)	7 (0.6)
Broken§ (1200)	0	0	0	0	0	0	23 (1.9)	0	0	0	6 (0.5)	1171 (97.6)

* Sample size, + Values expressed in percentage, † Canada Western Red Spring Wheat, ‡ Durum Wheat, ¥ wheathead, ¤wild buckwheat, § broken-wheat pieces.

Table 7.1(d) Confusion matrix of the model with twelve classes for the leave-one-out method (Non-parametric estimation)

Class (to)→ (from)↓	CWRS†	Durum‡	Barley	Rye	Oats	Whead¥	Chaff	Wildoats	Canola	wbwheat¤	Flax	Broken§	Other
CWRS † (3600)*	3591 (99.8+)	0	0	0	0	0	0	0	0	0	0	0	3 (0.3)
Durum ‡ (1200)	0	1198 (99.1)	0	9 (0.8)	0	0	0	0	0	0	0	0	2 (0.2)
Barley (1200)	0	10 (0.8)	1180 (98.3)	1 (0.8)	0	0	0	0	0	0	0	0	9 (0.8)
Rye (1200)	0	28 (2.3)	1 (0.1)	1166 (97.2)	0	0	0	0	0	0	0	0	5 (0.4)
Oats (1200)	0	0	0	0	1199 (99.9)	0	0	0	0	0	0	0	1 (0.1)
Whead¥ (1200)	0	0	0	0	0	1187 (98.9)	12 (1.0)	0	0	0	0	0	1 (0.1)
Chaff (1200)	0	0	0	0	0	13 (1.1)	1173 (97.8)	0	0	0	0	13 (1.1)	1 (0.1)
Wildoats (1200)	0	0	0	0	0	0	1 (0.1)	1198 (99.8)	0	0	0	0	1 (0.8)
Canola (1200)	0	0	0	0	0	0	0	0	1194 (99.5)	4 (0.3)	0	2 (0.2)	0
Wbwheat¤ (1200)	0	0	0	0	0	1 (0.1)	0	0	2 (0.2)	1196 (99.7)	0	0	1 (0.1)
Flax (1200)	0	0	0	0	0	0	0	0	0	0	1197 (99.8)	3 (0.3)	0
Broken § (1200)	0	0	0	0	0	0	13 (1.1)	0	0	0	0	1185 (98.8)	2 (0.2)

* Sample size, + Values expressed in percentage, † Canada Western Red Spring Wheat, ‡ Durum Wheat, ¥ wheathead, ¤ wild buckwheat, § broken-wheat pieces.

(98.8%)[Table7.1(d)].

When the leave-one-out method was used both with normal and non-parametric methods the classification accuracies of wheathead and chaff were considerably higher than when the hold-out method was used (>90% in comparison to <30%). This suggests that though these dockage classes are well separated from other classes in the model, the variations in these two classes were not well represented in the test data set used for the hold-out method. Moreover the ranges for the features in the wheathead class were large because both single and multiple wheatheads represented as the wheathead class. Therefore, the wheathead class was separated into two classes as the single- and multiple-wheathead for further analysis. Additional images of both single- and multiple wheatheads were taken and the features extracted were included in the data set.

7.2 Morphology-Colour Model Classifier with 13 Classes

When the leave-one-out method was used with normal estimation, the classification accuracies of were: CWRS wheat (99.3), durum wheat (94.7), barley (97.6), rye (95.8), oats (99.8), multiple-wheathead (96.7), chaff (83.3), wildoats (99.6), canola (99.4), wild buckwheat (98.2), flax (99.3), broken-wheat pieces (97.3), and single-wheathead (96.8%)[Table 7.2(a)]. For non-parametric estimation, the classification accuracies were: CWRS wheat (100.0), durum wheat (98.8), barley (98.6),rye (97.3), oats (100.0), multiple-wheathead (99.0), chaff (96.8), wildoats (99.8), canola (99.6), wild buckwheat (99.7), flax (99.8), broken-wheat pieces (98.8), and single-wheathead (98.9 %) [Table 7.2(b)]. The higher classification accuracies for the non-parametric estimation imply that the samples were not normally distributed.

When the hold-out method was used with normal estimation, the classification accuracies were: CWRS wheat (99.9), durum wheat (89.7), barley (96.0), rye (98.7), oats (99.3), multiple-wheathead (99.3), chaff (9.7), wildoats (99.0), canola (99.7), wild buckwheat (98.7), flax (99.3), broken-wheat pieces (98.0), and single-wheathead (95.0%) [Table 7.2(c)]. For the non-parametric estimation, the classification accuracies were: CWRS wheat (100.0), durum wheat (96.7), barley (98.3), rye (99.3), oats (99.3), mutiple-wheathead (100.0), chaff (21.7), wildoats (99.7), canola (100.0), wild buckwheat (100.0), flax (100.0), broken-wheat pieces (99.7), and single-wheathead (96.7%) [Table 7.2 (d)].

There was a significant increase in the classification accuracies for wheathead and chaff dockage classes over the model which used both single and multiple wheatheads as one class. Separation of the wheathead class into single- and multipl- wheathead resulted in higher classifications for these classes.

Hold-out method classifier is suitable for the industrial application because a classifier can be developed prior to implementation for testing and classifying objects on-line. The classification accuracies, however, were low for for chaff. When the hold-out method was used most of the chaff components were misclassified as oats because of the closeness of their features to the oats class. Inclusion of textural and additional colour features may result in better classification of the chaff class. All dockage components except chaff could be classified with >95% accuracy (Table 7.2 c, 7.2 d) by a machine vision system. Chaff should be removed by aspiration if machine vision system is to be used to optimize a cleaning unit.

Table 7.2(a) Confusion matrix of the model with thirteen classes for the leave-one-out method (Normal estimation)

Class (to)→ (from)↓	CWRS†	Durum‡	Barley	Rye	Oats	Mwhead¥	Chaff	Wildoats	Canola	wbwheat¤	Flax	Broken§	S-whead£
CWRS† (3600)*	3576 (99.3+)	0	0	19 (0.5)	0	5 (0.1)	0	0	0	0	0	0	0
Durum ‡ (1200)	8 (0.7)	1136 (94.7)	9 (0.6)	45 (3.6)	0	2 (0.2)	0	0	0	0	0	0	0
Barley (1200)	0	13 (1.1)	1170 (97.6)	14 (1.2)	0	3 (0.3)	0	0	0	0	0	0	0
Rye (1200)	0	38 (3.2)	10 (0.8)	1149 (95.8)	0	3 (0.3)	0	0	0	0	0		0
Oats (1200)	0	0	0	1 (0.1)	1197 (99.8)	2 (0.2)	0	0	0	0	0	0	0
Mwhead¥ (1200)	0	0	0	0	0	1160 (96.7)	0	0	0	0	0	0	40 (3.3)
Chaff (1200)	0	0	0	0	0	7 (0.6)	999 (83.3)	1 (0.1)	0	0	0	0	0
Wildoats (1200)	0	0	0	0	0	0	5 (0.4)	1195 (99.6)	0	0	0	0	0
Canola (1200)	0	0	0	0	0	0	4 (0.3)	0	1193 (99.4)	2 (0.2)	0	1 (0.1)	0
Wbwheat¤ (1200)	0	0	0	0	0	1 (0.1)	1 (0.1)	0	8 (0.7)	1178 (98.2)	2 (0.2)	10 (0.8)	0
Flax (1200)	0	0	0	0	0	0	1 (0.1)	0	0	0	1192 (99.3)	7 (0.6)	0
Broken (1200)	0	0	0	0	0	0	26 (2.2)	0	1 (0.1)	0	6 (0.5)	1167 (97.3)	0
S-whead£ (1200)	0	0	0	0	0	10 (0.8)	28 (2.3)	0	0	0	0	0	1163 (96.8)

* Sample size, + Values expressed in percentage, † Canada Western Red Spring Wheat, ‡ Durum Wheat, ¥ Multiple-wheathead, ¤ wild buckwheat, § broken-wheat pieces, £ Single-wheathead.

Table 7.2(b) Confusion matrix of the model with thirteen classes for the leave-one-out method (Non-parametric estimation)

Class(to)→ (from)↓	CWRS†	Durum‡	Barley	Rye	Oats	Mwhead¥	Chaff	Wildoats	Canola	wbwheat¤	Flax	Broken§	S-whead£	Other
CWRS † (3600)*	3600 (100+)	0	0	0	0	0	0	0	0	0	0	0	0	0
Durum ‡ (1200)	0	1185 (98.8)	1 (0.1)	12 (1.0)	0	0	0	0	0	0	0	0	0	2 (0.2)
Barley (1200)	0	9 (0.8)	1183 (98.6)	0	0	0	0	0	0	0	0	0	0	8 (0.7)
Rye (1200)	0	28 (2.3)	3 (0.3)	1167 (97.3)	0	0	0	0	0	0	0	0	0	2 (0.2)
Oats (1200)	0	0	0	0	1200 (100)	0	0	0	0	0	0	0	0	0
Mwhead¥ (1200)	0	0	0	0	2 (0.2)	1188 (99.0)	0	0	0	0	0	0	10 (0.8)	0
Chaff (1200)	0	0	0	0	0	0	1161 (96.8)	0	0	0	0	14 (1.2)	25 (2.1)	0
Wildoats (1200)	0	0	0	0	0	0	3 (0.3)	1197 (99.8)	0	0	0	0	0	0
Canola (1200)	0	0	0	0	0	0	0	0	1195 (99.6)	2 (0.2)	0	2 (0.2)	0	1 (0.1)
Wbwheat¤ (1200)	0	0	0	0	0	1 (0.1)	0	0	2 (0.2)	1196 (99.7)	0	0	0	1 (0.1)
Flax (1200)	0	0	0	0	0	0	0	0	0	0	1197 (99.8)	3 (0.3)	0	0
Broken § (1200)	0	0	0	0	0	0	13 (1.1)	0	0	0	0	1186 (98.8)	0	1 (0.1)
S-Whead£ (1200)	0	0	0	0	0	5 (0.4)	8 (0.7)	0	0	0	0	0	1188 (98.9)	0

* Sample size, + Values expressed in percentage, † Canada Western Red Spring Wheat, ‡ Durum Wheat, ¥ Multiple-wheathead, ¤ wild buckwheat, § broken-wheat pieces, £ Single-wheathead.

Table 7.2(c) Confusion matrix of the model with thirteen classes for the hold-out method (Normal estimation)

Class (to)→ (from)↓	CWRS†	Durum‡	Barley	Rye	Oats	Mwhead¥	Chaff	Wildoats	Canola	wbwheat¤	Flax	Broken§	S-whead£
CWRS† (900)*	899 (99.9+)	0	0	1 (0.1)	0	0	0	0	0	0	0	0	0
Durum ‡ (300)	0	269 (89.7)	8 (2.7)	23 (7.7)	0	0	0	0	0	0	0	0	0
Barley (300)	0	10 (3.3)	285 (95.0)	3 (1.0)	0	2 (0.7)	0	0	0	0	0	0	0
Rye (300)	1 (0.3)	3 (1.0)	0	296 (98.7)	0	0	0	0	0	0	0	0	0
Oats (300)	0	0	0	0	298 (99.3)	0	0	0	0	0	0	0	0
Mwhead¥ head(300)	0	0	0	0	0	298 (99.3)	0	0	0	0	0	0	2 (0.7)
Chaff (300)	5 (1.7)	0	0	31 (10.3)	81 (27.0)	154 (51.3)	29 (9.7)	0	0	0	0	0	0
Wildoats (300)	0	0	0	0	0	0	2 (0.7)	297 (99.0)	0	0	0	0	1 (0.3)
Canola (300)	0	0	0	0	0	0	0	0	299 (99.7)	0	0	1 (0.3)	0
Wbwheat¤ (300)	0	0	0	0	0	0	0	0	0	296 (98.7)	2 (0.7)	2 (0.7)	0
Flax (300)	0	0	0	0	0	0	0	0	0	0	298 (99.3)	2 (0.7)	0
Broken § (300)	0	0	0	0	0	0	5 (1.7)	0	0	0	1 (0.3)	294 (98.0)	0
S-Whead£ (300)	0	0	0	0	0	6 (2.0)	9 (3.0)	0	0	0	0	0	285 (95.0)

* Sample size, + Values expressed in percentage, † Canada Western Red Spring Wheat, ‡ Durum Wheat, ¥ Multiple-wheathead, ¤ wild buckwheat, § broken-wheat pieces, £ Single-wheathead.

Table 7.2(d) Confusion matrix of the model with thirteen classes for the hold-out method (Non-parametric estimation)

Class (to)→ (from)↓	CWRS†	Durum‡	Barley	Rye	Oats	Mwheat¥	Chaff	Wildoats	Canola	wbwheat¤	Flax	Broken§	S-wheat£	Other
CWRS† (900)*	900 (100+)	0	0	0	0	0	0	0	0	0	0	0	0	0
Durum‡ (300)	0	290 (96.7)	1 (0.3)	8 (2.7)	0	0	0	0	0	0	0	0	0	1 (0.3)
Barley (300)	0	4 (1.3)	295 (98.3)	0	0	0	0	0	0	0	0	0	0	1 (0.3)
Rye (300)	0	2 (0.7)	0	298 (99.3)	0	0	0	0	0	0	0	0	0	0
Oats (300)	1 (0.3)	0	0	1 (0.3)	298 (99.3)	0	0	0	0	0	0	0	0	0
Mwhead¥ (300)	0	0	0	0	0	300 (100)	0	0	0	0	0	0	0	0
Chaff (300)	20 (6.7)	0	0	0	211 (70.3)	3 (1.0)	65 (21.7)	0	0	0	0	0	0	1 (0.3)
Wildoats (300)	0	0	0	0	0	0	1 (0.3)	299 (99.7)	0	0	0	0	0	0
Canola (300)	0	0	0	0	0	0	0	0	300 (100)	0	0	0	0	0
Wbwheat¤ (300)	0	0	0	0	0	0	0	0	0	300 (100)	0	0	0	0
Flax (300)	0	0	0	0	0	0	0	0	0	0	300 (100)	0	0	0
Broken § (300)	0	0	0	0	0	0	1 (0.3)	0	0	0	0	299 (99.7)	0	0
S-Whead£ (300)	0	0	0	0	0	8 (2.7)	1 (0.3)	0	0	0	0	0	290 (96.7)	1 (0.3)

* Sample size, + Values expressed in percentage, † Canada Western Red Spring Wheat, ‡ Durum Wheat, ¥ Multiple-wheathead, ¤ wild buckwheat, § broken-wheat pieces, £ Single-wheathead.

7.3 Selection of Features

The features were arranged in the descending order of their level of contribution to

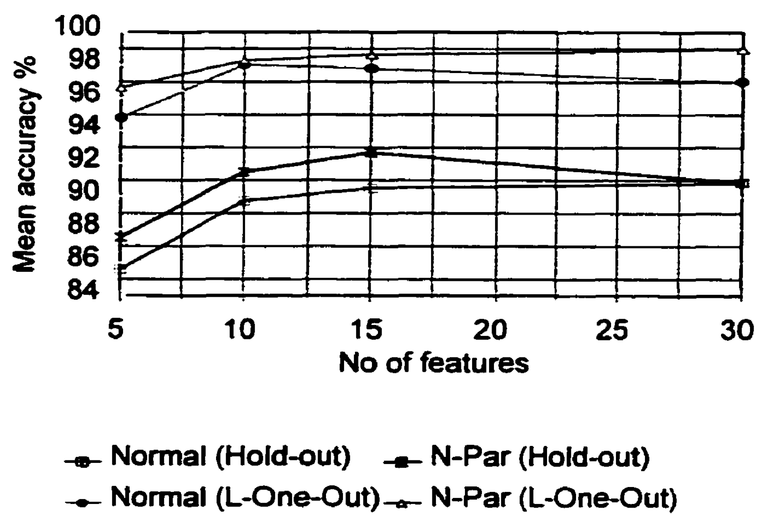


Figure 7.1 Comparison of classification accuracies with selected features

the classifier for both models (the model with twelve classes) [Table 7.3(a)] and (the model with thirteen classes) [Table 7.3(b)]. First Fourier magnitude was the most significant [average squared canonical correlation (ASCC) = 0.0773] and the average blue was the least significant (ASCC = 0.5278) feature used in the model with thirteen classes [Table 7.3(b)]. Discriminant analyses were carried out with the first 5, 10, and 15 features from Table 7.3(b) and the classification accuracies were compared with all 30 features (Fig. 7.1).

The classification summary for the first 5, 10, and 15 feature models are given in Appendix B. The individual rankings of the features are listed in Table 7.3(c). The between-class correlation coefficients are listed in Appendix C.

There are only two color features in the best 15 features [Table 7.3 (c)]. Therefore a

Table 7.3(a) Selection of features using STEPDISC analysis with twelve classes in the model

Number	Selected features	Average squared canonical correlation	Partial r^2
1	Length	0.0703	0.913
2	Average Red	0.1307	0.826
3	Average Green	0.1900	0.772
4	Haralick Ratio	0.2424	0.699
5	Rectangular Ratio	0.2885	0.642
6	First Fourier Magnitude	0.3288	0.645
7	Standard Deviation of radii	0.3711	0.969
8	Standard Deviation of Green	0.3846	0.328
9	Standard Deviation of Red	0.4063	0.317
10	Area Ratio	0.4195	0.243
11	Maximum Radius	0.4298	0.190
12	Second Invariant Moment	0.4338	0.191
13	First Invariant Moment	0.4333	0.305
14	Area	0.4480	0.125
15	Width	0.4584	0.280
16	Second Fourier Magnitude	0.4628	0.079
17	Intensity	0.4659	0.070
18	Thinnes Ratio	0.4678	0.058
19	Forth Invariant Moment	0.4697	0.050
20	Perimeter	0.4713	0.045
21	Third Fourier Magnitude	0.4730	0.034
22	Minimum Radius	0.4746	0.029
23	Radius Ratio	0.4756	0.032
24	Fourth Fourier Magnitude	0.4762	0.018
25	Standard Deviation of Blue	0.4769	0.011
26	Third Invariant Moment	0.4771	0.009
27	Length of Minor axis	0.4773	0.002
28	Aspect Ratio	0.4774	0.002
29	Length of Principal Axis	0.4775	0.001
30	Average Blue	0.4775	0.001

Table 7.3(b) **Selection of features using STEPDISC analysis with thirteen classes in the model**

Number	Selected features	Average squared canonical correlation	Partial r^2
1	First Fourier Magnitude	0.0773	0.928
2	Standard Deviation of Radii	0.1590	0.980
3	Average Red	0.2217	0.799
4	Rectangular Ratio	0.2842	0.760
5	Haralick Ratio	0.3399	0.686
6	Average Green	0.3899	0.620
7	Maximum Radius	0.4058	0.285
8	Area	0.4258	0.336
9	Width	0.4406	0.267
10	Standard Deviation of Green	0.4555	0.261
11	Standard Deviation of Red	0.4768	0.298
12	Second Invariant Moment	0.4847	0.221
13	First Invariant Moment	0.4935	0.309
14	Area Ratio	0.5007	0.158
15	Length	0.5055	0.101
16	Second Fourier Magnitude	0.5112	0.094
17	Intensity	0.5142	0.068
18	Thinnes Ratio	0.5163	0.066
19	Forth Invariant Moment	0.5182	0.045
20	Perimeter	0.5199	0.041
21	Third Fourier Magnitude	0.5213	0.035
22	Third Invariant Moment	0.5230	0.033
23	Radius Ratio	0.5238	0.025
24	Minimum Radius	0.5254	0.036
25	Length of Minor Axis	0.5259	0.023
26	Fourth Fourier Magnitude	0.5266	0.018
27	Aspect Ratio	0.5268	0.011
28	Standard Deviation of Blue	0.5272	0.007
29	Length of Principal Axis	0.5273	0.002
30	Average Blue	0.5278	0.001

Table 7.3(c) **Individual rankings of features using STEPDISC analysis with thirteen classes in the model**

Number	Selected features	Average squared canonical correlation	Partial r^2
1	First Fourier Magnitude	0.0773	0.928
2	Standard Deviation of Radii	0.0773	0.927
3	Length	0.0772	0.927
4	Maximum Radius	0.0769	0.923
5	Perimeter	0.0758	0.910
6	Area	0.0735	0.883
7	Average Red	0.0720	0.865
8	Average Green	0.0707	0.848
9	Rectangular Ratio	0.0700	0.840
10	Width	0.0693	0.832
11	First Invariant Moment	0.0678	0.814
12	Haralick Ratio	0.0659	0.791
13	Minimum Radius	0.0645	0.774
14	Second Fourier Magnitude	0.0644	0.773
15	Thinnes Ratio	0.0644	0.773
16	Length of Pricipal Axis	0.0635	0.763
17	Intensity	0.0631	0.758
18	Second Invariant Moment	0.0615	0.738
19	Area Ratio	0.0550	0.660
20	Length of Minor Axis	0.0481	0.578
21	Standard Deviation of Green	0.0426	0.512
22	Third Fourier Magnitude	0.0407	0.488
23	Fourth Fourier Magnitude	0.0370	0.444
24	Radius Ratio	0.0355	0.426
25	Average Blue	0.0324	0.389
26	Standard Deviation of Red	0.0318	0.382
27	Standard Deviation of Blue	0.0217	0.261
28	Fourth Invariant Moment	0.0175	0.210
29	Third Invariant Moment	0.0088	0.106
30	Aspect Ratio	0.0008	0.009

model with only morphological features was evaluated.

The classification accuracies were low when the first five features were used. The mean classification accuracy increased with the number of features upto the first 15 features selected from Table 7.3 (b) and remained constant thereafter except for the hold-out method with non-parametric analysis where it decreased slightly (Fig. 7.1). The addition of more features did not improve the performance of the classifier. It is important to note that the mean classification accuracy for the hold-out method with all 30 features in the model with thirteen classes was around 90% although 100% classification was achieved in many classes (CWRS wheat, Canola, Wild buckwheat, and flax). This was because the classification accuracy for chaff class was very poor. Additional colour features like the colour histogram. different combinations of R, G, and B, and textural features should be investigated for improving the classification accuracy of the chaff and the mean accuracy of the model.

The results of this study could be used to control a cleaner by a machine vision system. The impurities (dockage) at different stages of cleaning could be identified and the cleaner controlled accordingly.

Zayas et al. (1989) discriminated 33 wheat and 87 non-wheat components (foreign materials like wild buckwheat, glass, castor beans, yellow foxtail) from a sample of 34 wheat grains and 99 non-wheat components. They achieved 100% discrimination of wild buckwheat from wheat grains. In a later study, Zayas et al. (1990) identified all of the broken corn kernels from the whole corn kernels.

7.4 Morphology Model Classifier

A model (thirteen classes) with only morphological features was investigated to evaluate the ability of morphological features to discriminate the dockage classes from the cereal grain classes.

When the leave-one-out method was used with normal estimation the classification accuracies were: CWRS wheat (99.3), durum wheat (92.8), barley (95.3), rye (90.0), oats (99.8), multiple-wheathead (95.8), chaff (73.9), wildoats (98.7), canola (98.1), wild buckwheat (95.6), flax (98.3), broken-wheat pieces (85.0), and single-wheathead (97.2%) [Table 7.4(a)]. When the leave-one-out method with non-parametric estimation was used the classification accuracies were: CWRS wheat (100.0), durum wheat (95.1), barley (95.9), rye (91.8), oats (100.0), multiple-wheathead (98.2), chaff (93.6), wildoats (99.3), canola (98.9), wild buckwheat (97.3), flax (99.0), broken-wheat pieces (85.4), and single-wheathead (97.2%)[Table 7.4(b)].

For the hold-out method with normal estimation the classification accuracies were: CWRS wheat (100.0), durum wheat (83.0), barley (92.3), rye (95.7), oats (99.3), multiple-wheathead (98.3), chaff (8.7), wildoats (48.7), canola (98.7), wild buckwheat (95.3), flax (96.7), broken-wheat pieces (87.3), and single-wheathead (95.7%)[Table 7.4(c)]. For the hold-out method with non-parametric estimation the classification accuracies were: CWRS wheat (100.0), durum wheat (79.3), barley (97.3), rye (96.0), oats (99.7), multiple-wheathead (100.0), chaff (19.0), wildoats (94.3), canola (99.0), wild buckwheat (98.0), flax (98.3), broken-wheat pieces (87.3), and single-wheathead (94.0%)[Table 7.4 (d)].

The classification accuracies were reduced little when the basic color features were

Table 7.4(a) Confusion matrix of the morphology model with thirteen classes for the leave-one-out method (Normal estimation)

Class (to)→ (from)↓	CWRS†	Durum‡	Barley	Rye	Oats	Mwhead¥	Chaff	Wildoats	Canola	wbwheat¤	Flax	Broken§	S-whead£
CWRS † (3600)*	3575 (99.3+)	0	0	20 (0.6)	0	0	0	5 (0.1)	0	0	0	0	0
Durum ‡ (1200)	11 (0.9)	1114 (92.8)	10 (0.8)	63 (5.3)	0	2 (0.2)	0	0	0	0	0	0	0
Barley (1200)	0	25 (2.1)	1143 (95.3)	30 (2.5)	0	2 (0.2)	0	0	0	0	0	0	0
Rye (1200)	3 (0.3)	96 (8.3)	18 (1.5)	1080 (90.0)	0	3 (0.3)	0	0	0	0	0	0	0
Oats (1200)	0	0	0	1 (0.1)	1297 (99.8)	2 (0.2)	0	0	0	0	0	0	0
Mwhead¥ (1200)	0	0	0	0	0	1150 (95.8)	0	0	0	0	0	0	50 (4.2)
Chaff (1200)	0	0	0	0	0	6 (0.5)	887 (73.9)	1(0.1)	0	0	0	99 (8.3)	206 (17.2)
Wildoats (1200)	0	0	0	0	0	2 (0.2)	10 (0.8)	1184 (98.7)	0	0	0	0	4 (0.3)
Canola (1200)	0	0	0	0	0	0	4 (0.3%)	0	1177 (98.1)	11 (0.9)	0	8 (0.7)	0
Wbwheat¤ (1200)	0	0	0	0	0	0	3 (0.3)	0	11 (0.9)	1147 (95.6)	12 (1.0)	27 (2.3)	0
Flax (1200)	0	0	0	0	0	0	3 (0.3)	0	0	3 (0.3)	1180 (98.3)	14 (1.2)	0
Broken§ (1200)	0	0	0	0	0	0	33 (2.3)	0	11 (0.9)	70 (5.8)	66 (5.5)	1020 (85.0)	0
S-Whead£ (1200)	0	0	0	0	0	9 (0.8)	25 (2.08)	0	0	0	0	0	1167 (97.2)

* Sample size, + Values expressed in percentage, † Canada Western Red Spring Wheat, ‡ Durum Wheat, ¥ Multiple-wheathead, ¤ wild buckwheat, § broken-wheat pieces, £ Single-wheathead.

Table 7.4(b) Confusion matrix of the morphology model with thirteen classes for the leave-one-out method (Non-parametric estimation)

Class (to)→ (from)↓	CWRS†	Durum‡	Barley	Rye	Oats	Mwhead	Chaff	Wildoats	Canola	wbwheat¤	Flax	Broken§	S-wheat£	Other
CWRS† (3600)	3600 (100+)	0	0	0	0	0	0	0	0	0	0	0	0	0
Durum ‡ (1200)	0	1141 (95.1)	1 (0.1)	54 (4.5)	0	0	0	0	0	0	0	0	0	5 (0.4)
Barley (1200)	0	19 (1.6)	1151 (95.9)	5 (1.3)	0	0	0	0	0	0	0	0	0	15 (1.3)
Rye (1200)	0	84 (7.0)	7 (0.6)	1102 (91.8)	0	0	0	0	0	0	0	0	0	7 (0.6)
Oats (1200)	0	0	0	0	1200 (100)	0	0	0	0	0	0	0	0	0
Mwhead¥ (1200)	0	0	0	0	2 (0.2)	1178 (98.2)	0	0	0	0	0	0	19 (1.6)	1 (0.1)
Chaff (1200)	0	0	0	0	0	0	1123 (93.6)	6 (0.5)	0	0	1 (0.1)	22 (1.8)	41 (3.4)	7 (0.6)
Wildoats (1200)	0	0	0	0	0	0	7 (0.6)	1191 (99.3)	0	0	0	0	0	2 (0.2)
Canola (1200)	0	0	0	0	0	0	0	0	1187 (98.9)	9 (0.6)	0	0	0	4 (0.3)
wbwheat¤ (1200)	0	0	0	0	0	1 (0.1)	0	0	11 (0.9)	1167 (97.3)	3 (0.3)	8 (0.7)	0	10 (0.8)
Flax (1200)	0	0	0	0	0	0	0	0	0	3 (0.3)	1188 (99.0)	4 (0.3)	0	4 (0.3)
Broken§ (1200)	0	0	0	0	0	0	25 (2.1)	0	3 (0.3)	60 (5.0)	68 (5.7)	1025 (85.4)	0	19 (1.6)
S-Whead£ (1200)	0	0	0	0	0	8 (0.7)	10 (1.7)	4 (0.3)	0	0	0	0	1167 (97.2)	2 (0.2)

* Sample size, + Values expressed in percentage, † Canada Western Red Spring Wheat, ‡ Durum Wheat, ¥ Multiple-wheathead, ¤ wild buckwheat, § broken-wheat pieces, £ Single-wheathead.

Table 7.4(c) Confusion matrix of the morphology model with thirteen classes for the hold-out method (Normal estimation)

Class (to)→ (from)↓	CWRS†	Durum‡	Barley	Rye	Oats	Mwhead¥	Chaff	Wildoats	Canola	wbwheat¤	Flax	Broken§	S-wheat£
CWRS † (900)*	900 (100+)	0	0	0	0	0	0	0	0	0	0	0	0
Durum‡ (300)	0	249 (83.0)	9 (3.0)	42 (14.0)	0	0	0	0	0	0	0	0	0
Barley (300)	1 (0.3)	16 (5.3)	277 (92.3)	4 (1.3)	0	2 (0.7)	0	0	0	0	0	0	0
Rye (300)	1 (0.3)	12 (4.0)	0	287 (95.7)	0	0	0	0	0	0	0	0	0
Oats (300)	0	0	0	0	298 (99.3)	2 (0.7)	0	0	0	0	0	0	0
Mwhead¥ (300)	0	0	0	0	0	295 (98.3)	0	0	0	0	0	0	5 (1.7)
Chaff (300)	4 (1.3)	0	0	31 (10.3)	82 (27.3)	157 (52.3)	26 (8.7)	0	0	0	0	0	0
Wildoats (300)	0	0	0	0	0	0	119 (39.7)	146 (48.7)	0	0	0	0	35 (11.7)
Canola (300)	0	0	0	0	0	0	0	0	296 (98.7)	2 (0.7)	0	2 (0.7)	0
Wbwheat¤ (300)	0	0	0	0	0	0	1 (0.3)	0	1 (0.3)	286 (95.3)	7 (2.3)	5 (1.7)	0
Flax (300)	0	0	0	0	0	0	0	0	0	2 (0.7)	290 (96.7)	8 (2.7)	0
Broken § (300)	0	0	0	0	0	0	6 (2.0)	0	3 (1.0)	19 (6.3)	10 (3.3)	262 (87.3)	0
S-Wheat£ (300)	0	0	0	0	0	6 (2.0)	7 (2.3)	0	0	0	0	0	287 (95.7)

* Sample size, + Values expressed in percentage, † Canada Western Red Spring Wheat, ‡ Durum Wheat, ¥ Multiple-wheathead, ¤ wild buckwheat, § broken-wheat pieces, £ Single-wheathead.

Table 7.4(d) Confusion matrix of the morphology model with thirteen classes for the hold-out method (Non-parametric estimation)

Class (to)→ (from)↓	CWRS †	Durum ‡	Barley	Rye	Oats	Mwhead ¥	Chaff	Wildoats	Canola	wbwheat ¤	Flax	Broken §	S-whead £	Other
CWRS † (900)*	900 (100+)	0	0	0	0	0	0	0	0	0	0	0	0	0
Durum ‡ (300)	0	238 (79.3)	14 (4.7)	38 (12.7)	0	0	0	0	0	0	0	0	0	10 (3.3)
Barley (300)	0	3 (1.0)	292 (97.3)	2 (0.7)	0	0	0	0	0	0	0	0	0	3 (1.0)
Rye (300)	0	12 (4.0)	0	288 (96.0)	0	0	0	0	0	0	0	0	0	0
Oats (300)	1 (0.3)	0	0	0	299 (99.7)	0	0	0	0	0	0	0	0	0
Mwhead¥ (300)	0	0	0	0	0	300 (100)	0	0	0	0	0	0	0	0
Chaff (300)	29 (9.7)	0	0	0	207 (69.0)	3 (1.0)	57 (19.0)	0	0	0	0	1 (0.3)	1 (0.3)	2 (0.7)
Wildoats (300)	0	0	0	0	0	0	14 (4.7)	283 (94.3)	0	0	0	0	1 (0.3)	2 (0.7)
Canola (300)	0	0	0	0	0	0	0	0	297 (99.0)	3 (1.0)	0	0	0	0
Wbwheat¤ (300)	0	0	0	0	0	0	0	0	1 (0.3)	294 (98.0)	2 (0.7)	1 (0.3)	0	2 (0.7)
Flax (300)	0	0	0	0	0	0	0	0	0	2 (0.7)	295 (98.3)	3 (1.0)	0	0
Broken§ (300)	0	0	0	0	0	0	8 (2.7)	0	1 (0.3)	15 (5.0)	12 (4.0)	262 (87.3)	0	2 (0.7)
S-Whead£ (300)	0	0	0	0	0	10 (3.3)	8 (2.7)	0	0	0	0	0	282 (94.0)	0

* Sample size, + Values expressed in percentage, † Canada Western Red Spring Wheat, ‡ Durum Wheat, ¥ Multiple-wheathead, ¤ wild buckwheat, § broken-wheat pieces, £ Single-wheathead.

removed from the model. The classification accuracy for the durum wheat class was reduced as its bright color might have improved its classification in the morphology-color model.

7.5 Colour Model Classifier

A colour model (with 13 classes) was investigated to test the discrimination power of the basic colour features. When the leave-one-out method with normal estimation was used, the classification accuracies were: CWRS wheat (65.9), durum wheat (65.1), barley (81.3), rye (74.1), oats (31.3), multiple-wheathead (58.3), chaff (75.9), wildoats (60.3), canola (95.1), wild buckwheat (96.7), flax (51.9), broken-wheat pieces (85.8), and single-wheathead (56.4%) [Table 7.5(a)]. When non-parametric estimation was used in the leave-one-out method the classification accuracies were: CWRS wheat (78.5), durum wheat (77.4), barley (84.3), rye (85.7), oats (75.4), multiple-wheathead (72.2), chaff (81.9), wildoats (94.2), canola (84.0), wild buckwheat (92.8), flax (95.9), broken-wheat pieces (78.6), and single-wheathead (56.1%)[Table 7.5(b)].

For the hold-out method with the normal estimation the classification accuracies were: CWRS wheat (77.7), durum wheat (74.7), barley (65.0), rye (70.0), oats (0.0), multiple-wheathead (71.7), chaff (34.0), wildoats (46.3), canola (96.3), wild buckwheat (99.0), flax (52.3), broken-wheat pieces (82.7), and single-wheathead (55.7%) [Table 7.5(c)]. When the hold-out method with non-parametric estimation was used the classification accuracies were: CWRS wheat (71.6), durum wheat (88.0), barley (51.0), rye (75.0), oats (2.7), multiple-wheathead (81.7), chaff (50.0), wildoats (94.7), canola (83.7), wild buckwheat (96.7), flax (95.3), broken-wheat pieces (78.3), and single-wheathead (59.0%) [Table 7.5(d)].

Table 7.5(a) Confusion matrix of the colour model with thirteen classes for the leave-one-out method (Normal estimation)

Class (to)→ (from)↓	CWRS†	Durum‡	Barley	Rye	Oats	Mwhead¥	Chaff	Wildoats	Canola	wbwheat¤	Flax	Broken§	S-wheat£
CWRS † (3600)	2371 (65.9+)	436 (12.1)	7 (0.2)	104 (2.9)	91 (2.5)	12 (0.3)	0	2 (0.1)	0	0	17 (0.5)	535 (14.9)	25 (0.7)
Durum‡ (1200)	269 (22.4)	781 (65.1)	72 (6.0)	2 (0.2)	68 (5.7)	8 (0.7)	0	0	0	0	0	0	0
Barley (1200)	14 (1.2)	56 (4.7)	976 (81.3)	27 (2.3)	26 (2.2)	46 (3.8)	1 (0.1)	1 (0.1)	0	0	0	0	53 (4.4)
Rye (1200)	159 (13.3)	5 (0.4)	11 (0.9)	889 (74.1)	44 (3.7)	3 (0.3)	0	26 (2.2)	0	0	11 (0.9)	50 (4.2)	5 (0.4)
Oats (1200)	227 (18.9)	81 (6.6)	100 (8.3)	30 (2.5)	375 (31.3)	207 (17.3)	9 (0.8)	0	0	0	0	2 (0.2)	169 (14.1)
Mwhead¥ (1200)	8 (0.7)	16 (1.3)	26 (2.2)	2 (0.2)	58 (4.8)	699 (58.3)	18 (1.5)	0	0	0	0	185 (15.4)	188 (15.7)
Chaff (1200)	0	0	0	3 (0.3)	31 (2.6)	73 (6.1)	911 (75.9)	1 (0.1)	0	0	0	111 (9.3)	71 (5.9)
Wildoats (1200)	10 (0.8)	0	0	38 (3.2)	1 (0.1)	0	0	724 (60.3)	382 (31.8)	24 (2.0)	16 (1.3)	5 (0.4)	0
Canola (1200)	8 (0.7)	4 (0.3)	0	0	1 (0.1)	0	0	7 (0.6)	1141 (95.1)	29 (2.4)	10 (0.8)	0	0
Wbwheat¤ (1200)	0	0	0	0	0	0	0	22 (1.8)	18 (1.5)	1160 (96.7)	0	0	0
Flax (1200)	7 (0.6)	0	0	1 (0.1)	0	0	0	5 (0.4)	563 (46.9)	0	623 (51.9)	0	1 (0.1)
Broken § (1200)	25 (2.1)	1 (0.1)	15 (1.3)	1 (0.1)	5 (0.4)	15 (1.3)	34 (2.8)	0	0	0	0	1029 (85.8)	75 (6.3)
S-Whead£ (1200)	22 (1.8)	2 (0.2)	9 (0.8)	3 (0.3)	26 (2.2)	209 (17.4)	51 (4.3)	0	0	0	0	202 (16.8)	677 (56.3)

* Sample size, + Values expressed in percentage, † Canada Western Red Spring Wheat, ‡ Durum Wheat, ¥ Multiple-wheathead, ¤ wild buckwheat, § broken-wheat pieces, £ Single-wheathead.

Table 7.5(b) Confusion matrix of the colour model with thirteen classes for the leave-one-out method (Non-parametric estimation)

Class (to)→ (from)↓	CWRS†	Durum‡	Barley	Rye	Oats	Mwhead¥	Chaff	Wildoats	Canola	wbwheat¤	Flax	Broken§	S-whead£	Other
CWRS † (3600)*	2827 (78.5✚)	369 (10.3)	10 (0.3)	141 (3.9)	87 (2.4)	21 (0.6)	1 (0.0)	1 (0.0)	0	0	2 (0.1)	90 (2.5)	14 (0.4)	37 (1.0)
Durum ‡ (1200)	112 (9.3)	929 (77.4)	38 (3.2)	2 (0.2)	95 (7.9)	9 (0.6)	0	0	0	0	0	0	1 (0.1)	14 (1.2)
Barley (1200)	2 (0.2)	52 (4.3)	1011 (84.3)	20 (1.7)	83 (6.9)	7 (0.6)	0	0	0	0	0	2 (0.2)	14 (1.2)	9 (0.8)
Rye (1200)	80 (6.7)	12 (1.0)	11 (0.9)	1028 (85.7)	26 (2.2)	0	1 (0.1)	20 (1.7)	0	0	3 (0.3)	6 (0.5)	4 (0.3)	9 (0.6)
Oats (1200)	9 (0.8)	50 (4.2)	62 (5.2)	16 (1.3)	905 (75.4)	83 (6.9)	2 (0.2)	0	0	0	0	7 (0.6)	52 (4.3)	14 (1.2)
Mwhead¥ (1200)	2 (0.2)	6 (0.5)	18 (1.5)	0	91 (7.6)	866 (72.2)	30 (2.5)	0	0	0	0	36 (3.0)	142 (11.8)	9 (0.8)
Chaff (1200)	1 (0.1)	0	0	4 (0.3)	3 (0.3)	89 (7.4)	983 (81.9)	6 (0.5)	0	0	0	53 (4.4)	62 (5.2)	5 (0.4)
Wildoats (1200)	3 (0.3)	0	0	20 (1.7)	0	0	0	1130 (94.2)	8 (0.7)	32 (2.7)	6 (0.5)	0	0	1 (0.1)
Canola (1200)	6 (0.5)	2 (0.2)	0	2 (0.2)	0	0	0	27 (2.3)	1008 (84.0)	44 (3.7)	108 (9.0)	0	0	3 (0.3)
wbwheat¤ (1200)	0	0	0	0	0	0	0	55 (4.6)	30 (2.5)	1114 (92.8)	0	0	0	1 (0.1)
Flax (1200)	3 (0.3)	0	0	1 (0.1)	0	0	0	0	25 (2.1)	0	1151 (95.9)	0	0	1 (0.1)
Broken§ (1200)	61 (5.1)	1 (0.1)	4 (0.3)	4 (0.3)	10 (0.8)	53 (4.4)	42 (3.5)	0	0	0	0	943 (78.6)	77 (6.4)	5 (0.4)
S-whead£ (1200)	7 (0.6)	2 (0.2)	15 (1.3)	3 (0.3)	39 (3.3)	224 (18.7)	48 (4.0)	4 (0.3)	0	0	0	45 (3.8)	674 (56.1)	144 (12.0)

* Sample size, ✚ Values expressed in percentage, † Canada Western Red Spring Wheat, ‡ Durum Wheat, ¥ Multiple-wheathead, ¤ wild buckwheat, § broken-wheat pieces, £ Single-wheathead.

Table 7.5(c) Confusion matrix of the colour model with thirteen classes for the hold-out method (Normal estimation)

Class (to)→ (from)↓	CWRS†	Durum‡	Barley	Rye	Oats	Mwhead¥	Chaff	Wildoats	Canola	wbwheat¤	Flax	Broken§	S-whead£
CWRS † (900)*	699 (77.7✢)	91 (10.1)	1 (0.1)	13 (1.4)	78 (8.7)	2 (0.2)	0	1 (0.1)	0	0	3 (0.3)	10 (1.1)	2 (0.2)
Durum‡ (300)	47 (15.7)	224 (74.7)	28 (9.3)	1 (0.3)	0	0	0	0	0	0	0	0	0
Barley (300)	16 (5.3)	18 (6.0)	195 (65.0)	9 (3.0)	1 (0.3)	33 (11.0)	0	0	0	0	0	0	28 (9.3)
Rye (300)	37 (12.3)	0	8 (2.7)	210 (70.0)	10 (3.3)	0	0	24 (8.0)	0	0	10 (3.3)	1 (0.3)	0
Oats (300)	2 (0.7)	0	1 (0.3)	0	0	156 (52.0)	16 (5.3)	0	0	0	0	82 (27.3)	43 (14.3)
Mwhead¥ (300)	0	0	0	0	0	215 (71.7)	0	0	0	0	0	34 (11.3)	51 (17.0)
Chaff (300)	0	0	6 (2.0)	12 (4.0)	62 (20.7)	6 (2.0)	102 (34.0)	0	0	0	0	40 (13.3)	72 (24.0)
Wildoats (300)	6 (2.0)	0	0	11 (3.7)	0	0	0	139 (46.3)	139 (46.3)	4 (1.3)	0	1 (0.3)	0
Canola (300)	4 (1.3)	0	0	0	1 (0.3)	0	0	1 (0.3)	289 (96.3)	5 (1.7)	0	0	0
Wbwheat¤ (300)	0	0	0	0	0	0	0	3 (1.0)	0	297 (99.0)	0	0	0
Flax (300)	2 (0.7)	0	0	0	0	0	0	3 (1.0)	138 (46.0)	0	157 (52.3)	0	0
Broken§ (300)	8 (2.7)	0	2 (0.7)	0	3 (1.0)	6 (2.0)	11 (3.7)	0	0	0	0	248 (82.7)	22 (7.3)
S-Whead£ (300)	11 (3.7)	1 (0.3)	4 (1.3)	0	25 (8.3)	29 (9.7)	1 (0.3)	0	0	0	0	62 (20.7)	167 (55.7)

* Sample size, ✢ Values expressed in percentage, † Canada Western Red Spring Wheat, ‡ Durum Wheat, ¥ Multiple-wheathead, ¤ wild buckwheat, § broken-wheat pieces, £ Single-wheathead.

Table 7.5(d) Confusion matrix of the colour model with thirteen classes for the hold-out method (Non-parametric estimation)

Class (to)→ (from)↓	CWRS†	Durum‡	Barley	Rye	Oats	Mwhead¥	Chaff	Wildoats	Canola	wbwheat¤	Flax	Broken§	S-wheat£	Other
CWRS † (900)*	644 (71.6✚)	77 (8.6)	4 (0.4)	29 (3.2)	77 (8.6)	7 (0.8)	0	0	0	0	0	1 (0.1)	1 (0.1)	60 (6.7)
Durum ‡ (300)	18 (6.0)	264 (88.0)	8 (2.7)	1 (0.3)	0	0	0	0	0	0	0	0	0	9 (3.0)
Barley (300)	1 (0.3)	29 (9.7)	153 (51.0)	9 (3.0)	45 (15.0)	14 (4.7)	0	0	0	0	0	1 (0.3)	8 (2.7)	40 (13.3)
Rye (300)	29 (9.7)	6 (2.0)	7 (2.3)	225 (75.0)	2 (0.7)	0	0	16 (5.3)	0	0	1 (0.3)	0	0	14 (4.7)
Oats (300)	2 (0.7)	0	2 (0.7)	0	8 (2.7)	172 (57.3)	9 (3.0)	0	0	0	0	40 (13.3)	52 (17.3)	15 (5.0)
Mwhead¥ (300)	0	0	0	0	4 (1.3)	245 (81.7)	2 (0.7)	0	0	0	0	11 (3.7)	22 (7.3)	16 (5.3)
Chaff (300)	0	0	7 (2.3)	4 (1.3)	38 (12.7)	15 (5.0)	150 (50.0)	0	0	0	0	15 (5.0)	49 (16.3)	22 (7.3)
Wildoats (300)	1 (0.3)	0	0	5 (1.7)	0	0	0	284 (94.7)	2 (0.7)	4 (1.3)	1 (0.3)	0	0	3 (1.0)
Canola (300)	2 (0.7)	1 (0.3)	0	0	0	0	0	6 (2.0)	251 (83.7)	5 (1.7)	32 (10.7)	0	0	3 (1.0)
Wbwheat¤ (300)	0	0	0	0	0	0	0	7 (2.3)	2 (0.7)	290 (96.7)	0	0	0	1 (0.3)
Flax (300)	0	0	0	0	0	0	0	7 (2.3)	2 (0.7)	0	286 (95.3)	0	0	5 (1.7)
Broken§ (300)	8 (2.7)	0	0	1 (0.3)	2 (0.7)	14 (4.7)	10 (3.3)	0	0	0	0	235 (78.3)	14 (4.7)	16 (5.3)
S-Wheat£ (300)	6 (2.0)	2 (0.7)	7 (2.3)	0	21 (7.0)	55 (18.3)	7 (2.3)	0	0	0	0	11 (3.7)	177 (59.0)	14 (4.7)

* Sample size, ✚ Values expressed in percentage, † Canada Western Red Spring Wheat, ‡ Durum Wheat, ¥ Multiple-wheathead, ¤ wild buckwheat, § broken-wheat pieces, £ Single-wheathead.

The classification accuracies for the color model were very poor. A model with only basic color features is not helpful in discriminating the dockage components from wheat.

There is little difference between the classification accuracies of the morphology-color model and the morphology model, therefore, the morphology model can be used to discriminate the dockage components from wheat (Table 7.6). This would allow the use of a black and white camera to acquire the grey level images which will simplify the system and its cost.

Table 7.6. Summary of classification accuracies for different models and different analysis methods

Model	Analysis Method	CWRS ✣	Durum ⊗	Barley	Rye	Oats	Mwhead ✿	Chaff	Wildoats	Canola	Wbwheat ♦	Flax	Broken ✤	S-whead §	Mean
Morphology-Color 12†	Leave-one-out														
	Normal	99.2‡	96.6	98.2	96.3	99.8	96.3	92.6	99.8	99.4	98.5	99.3	97.6	-¶	97.8
	Non-par♣	99.8	99.1	98.3	97.2	99.9	98.9	97.8	99.8	99.5	99.7	99.8	98.8	-	99.1
	Holdout														
	Normal	99.7	89.7	95.3	99.0	99.7	27.3	30.0	99.3	99.7	98.7	99.3	98.0	-	86.3
	Non-par	100.0	97.3	98.7	99.3	99.3	2.3	12.0	99.7	100.0	100.0	100.0	100.0	-	84.1
Morphology 13	Leave-one-out														
	Normal	99.3	92.8	95.3	90.0	99.8	95.8	73.9	98.7	98.1	95.6	98.3	85.0	97.2	93.8
	Non-par	100.0	95.1	95.9	91.8	100.0	98.2	93.6	99.3	98.9	97.3	99.0	85.4	97.2	96.3
	Holdout														
	Normal	100.0	83.0	92.3	95.7	99.3	98.3	8.7	48.7	98.7	95.3	96.7	87.3	95.7	84.6
	Non-par	100.0	79.3	97.3	96.0	99.7	100.0	19.0	94.3	99.0	98.0	98.3	87.3	94.0	89.4
Color -13	Leave-one-out														
	Normal	65.9	65.1	81.3	74.1	31.3	58.3	75.9	60.3	95.1	96.7	51.9	85.8	56.3	69.0
	Non-par	78.5	77.4	84.3	85.7	75.4	72.2	81.9	94.2	84.0	92.8	95.9	78.6	56.1	81.3
	Holdout														
	Normal	77.7	74.7	65.0	70.0	0	71.7	34.0	46.3	96.3	99.0	52.3	82.7	55.7	63.5
	Non-par	71.6	88.0	51.0	75.0	2.7	81.7	50.0	94.7	83.7	96.7	95.3	78.3	59.0	71.4
Morphology-Color-13	Leave-one-out														
	Normal	99.3	94.7	97.6	95.8	99.8	96.7	83.3	99.6	99.4	98.2	99.3	97.3	96.8	96.8
	Non-par	100.0	98.8	98.6	97.3	100.0	99.0	96.8	99.8	99.6	99.7	99.8	98.8	98.9	99.0
	Holdout														
	Normal	99.9	89.7	95.0	98.7	99.3	99.3	9.7	99.0	99.7	98.7	99.3	98.0	95.0	90.9
	Non-par	100.0	96.7	98.3	99.3	99.3	100.0	21.7	99.7	100.0	100.0	100.0	99.7	96.7	93.2

✣ Canada Western Red Spring Wheat, ⊗ Durum Wheat, ✿ Multiple-wheathead, ♦ wild buckwheat, ✤ Broken-wheat pieces, § Single-wheathead, ‡ Values expressed in percentage, † Number of classes in the model, ¶ Single-wheatheads were included in the multiple-wheathead class, ♣ Non parametric estimation.

CHAPTER 8: CONCLUSIONS

For determination of physical quality of wheat samples by machine vision, dockage constituents have to be identified and classified. In this study, discrimination capabilities of morphological and basic color features were evaluated for identification of dockage constituents from CWRS wheat and other cereal grains. Morphology-colour, Morphology, and Colour models were developed and compared.

Based on this study, the following conclusions were made:

1) Division of wheathead into single- and multiple wheatheads improved the classification of wheathead class from <30% to >95%.

2) The model with only color features was not sufficient to discriminate the dockage components from wheat (mean classification accuracy was about 70%).

3) The morphology model discriminated the dockage components with >90.0% classification accuracies.

4) When the morphology model with thirteen classes was tested on an independent data set the classification accuracies were: CWRS wheat (100.0), durum wheat (79.3), barley (97.3), rye (96.0), oats (99.7), multiple-wheathead (100.0), chaff (19.0), wildoats (94.3), canola (99.0), wild buckwheat (98.0), flax (98.3), broken-wheat pieces (87.3), and single-wheathead (94.0%). The classification accuracies for the morphology- color model were: CWRS wheat (100.0), durum wheat (96.7), barley (98.3), rye (99.3), oats (99.3), multiple-wheathead (100.0), chaff (21.7), wildoats (99.7), canola (100.0), wild buckwheat (100.0), flax (100.0), broken-wheat pieces (99.7), and single-wheathead (96.7%).

5) The morphology-colour model improved the mean classification accuracy by 1.3% when tested on an independent data set.

6) It is necessary to improve the classification accuracy of chaff for practical implementation.

IX. REFERENCES

Anonymous. 1987. *Official Grain Grading Guide*. Winnipeg, MB: Canadian Grain Commission.

Anonymous. 1994. *Official Grain Grading Guide*. Winnipeg, MB: Canadian Grain Commission.

Barker, D.A., T.A. Vouri, M.R. Hegedus, and D.G. Myers. 1992a. The use of ray parameters for the discrimination of Australian wheat varieties. *Plant Varieties and Seeds* 5:35-45.

Barker, D.A., T.A. Vouri, and D.G. Myers. 1992b. The use of slice and aspect ratio parameters for the discrimination of Australian wheat varieties. *Plant Varieties and Seeds* 5:47-52.

Barker, D.A., T.A. Vouri, and D.G. Myers. 1992c. The use of Fourier descriptors for the discrimination of Australian wheat varieties. *Plant Varieties and Seeds* 5:93-102.

Barker, D.A., T.A. Vouri, M.R. Hegedus, and D.G. Myers. 1992d. The use of Chebychev coefficients for the discrimination of Australian wheat varieties. *Plant Varieties and Seeds* 5:103-111.

Baxes, G.A. 1994. *Digital Image Processing — Principles and Applications*. New York, NY: John Wiley and Sons, Inc.

Canada Grains Council. 1994. *Statistical Handbook*. Winnipeg, MB: Canada Grains Council.

Chen, C., Y.P. Chiang, and Y. Pomeranz. 1989. Image analysis and characterization of cereal grains with a laser range finder and camera contour extractor. *Cereal Chemistry* 66: 466-470.

Ding, K., R.V. Morey, W.F. Wilcke, and D.J. Hansen. 1990. Corn quality evaluation with computer vision. ASAE Paper No. 90-3532. St. Joseph, MI: ASAE.

Draper, S.R. and A.J. Travis. 1984. Preliminary observations with a computer based system for analysis of the shape of seeds and vegetative structures. *Journal of the National Institute of Agricultural Botany* 16:387-395.

Duda, R.O. and P.E. Hart. 1973. *Pattern Classification and Scene Analysis*. New York, NY: John Wiley and Sons, Inc.

Gonzalez, R.C. and R.E. Woods. 1992. *Digital Image Processing*. Reading, MA: Addison-Wesley Publishing Co.

Hand, D.J. 1981. *Discrimination and Classification*. New York, NY: John Wiley and Sons. Inc.

Hehn, J.L. and S. Sokhansanj. 1990. Canola and mustard seed identification using macintosh based imaging system. ASAE Paper No. 90-3534. St. Joseph, MI: ASAE.

Keefe, P.D. 1992. A dedicated wheat grading system. *Plant Varieties and Seeds* 5:27-33.

Keefe, P.D. and S.R. Draper. 1986. The measurement of new characters for cultivar identification in wheat using machine vision. *Seed Science and Technology* 14:715-724.

Keefe, P.D. and S.R. Draper. 1988. An automated machine vision system for the morphometry of new cultivars and plant genebank accessions. *Plant Varieties and Seeds* 1:1-11.

Kohler, J.M. 1991. Study of commercial grades of Canada Red Spring Wheat by digital image processing. Unpublished M.Sc. thesis. Department of Electrical and Computer Engineering, University of Manitoba, Winnipeg, MB.

Lai, F.S., I. Zayas, and Y. Pomeranz. 1986. Application of pattern recognition techniques in the analysis of cereal grains. *Cereal Chemistry* 63: 168-172.

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

Majumdar, S., D.S. Jayas, S.J. Symons, and N.R. Bulley. 1996b. Textural features for automated grain identification. CSAE Paper No. 96-611. Saskatoon, SK :CSAE.

Myers, D.G. and K.J. Edsall. 1989. The application of image processing techniques to the identification of Australian wheat varieties. *Plant Varieties and Seeds* 2: 109-116.

Neuman, M., H.D. Sapirstein, E. Shwedyk, and W. Bushuk. 1987. Discrimination of wheat class and variety by digital image analysis of whole grain samples. *Journal of Cereal Science* 6:125-132.

Neuman, M., H.D. Sapirstein, E. Shwedyk, and W. Bushuk. 1989a. Wheat grain color analysis by digital image processing: I. Methodology. *Journal of Cereal Science* 10:175-182.

Neuman, M., H.D. Sapirstein, E. Shwedyk, and W. Bushuk. 1989b. Wheat grain color analysis by digital image processing: II. Wheat class discrimination. *Journal of Cereal Science* 10:183-188.

Parker, J.R. 1994. *Practical Computer Vision using C*. New York, NY: John Wiley and Sons, Inc.

Parzen, E. 1962. On estimation of a probability density function and mode. *Annals of Mathematical*

Statistics 8:247-263.

Putnam, D.F. and R.G. Putnam. 1970. *Canada : A Regional Analysis*. Toronto, ON: J.M. Dent and Sons, Inc.

Rao, C.R. 1973. *Linear Statistical Inference and Its Applications*, 2d ed. New York, NY: John Wiley and Sons, Inc.

Rosenblatt, M. 1956. Remarks on some nonparametric estimates of a density function. *Annals of Mathematical Statisrics* 27:632-837.

Sapirstein, H.D. and W. Bushuk. 1989. Quantitative determination of foreign material and vitreosity in wheat by digital image analysis. In: H. Salovaara (ed.). *ICC '89 Symposium: Wheat End-Use Properties* 453-474. Lahti, Finland.

Sapirstein, H.D., M. Neuman, E.H. Wright, E. Shwedyk, and W. Bushuk. 1987. An instrumental system for cereal grain classification using digital image analysis. *Journal of Cereal Science* 6:3-14.

SAS. 1990. *SAS User's Guide: Statistics*. Raleigh, NC: Statistical Analysis System, Inc.

Segerlind, L. and B. Weinberg. 1972. Grain kernel identification by profile analysis. ASAE Paper No. 72-314. St. Joseph, MI:ASAE.

Shatadal, P., D.S. Jayas, and N.R. Bulley. 1995a. Digital image analysis for software separation and classification of touching grains:I.Disconnect algorithm. *Transactions of the ASAE* 38:635-643.

Shatadal, P., D.S. Jayas, and N.R. Bulley. 1995b. Digital image analysis for software separation and classification of touching grains:II.Classification. *Transactions of the ASAE* 38:645-649.

Shashidhar, N.S., D.S. Jayas, T.G. Crowe, and N.R. Bulley. 1996. Extraction of morphological features by ellipse fitting. CSAE Paper No. 96-610. Saskatoon, SK :CSAE.

Silverman, B.W. 1986. *Density Estimation for Statistics and Data Analysis*. New York, NY: Chapman and Hall.

Symons, S.J. and R.G. Fulcher. 1988a. Determination of wheat kernel morphological variation by digital image analysis: I. Variation in Eastern Canadian milling quality wheats. *Journal of Cereal Science* 8:211-218.

Symons, S.J. and R.G. Fulcher. 1988b. Determination of wheat kernel morphological variation by digital image analysis: II. Variation in cultivars of soft white winter wheats. *Journal of Cereal Science* 8:219-229.

Thomson W.H. and Y. Pomeranz. 1991. Classification of wheat kernels using three-dimensional image analysis. *Cereal Chemistry* 68: 357-361.

Travis, A.J. and S.R. Draper. 1985. A computer based system for the recognition of seed shape. *Seed Science and Technology* 13:813-820.

Zayas, I., Y. Pomeranz, and F.S. Lai. 1985. Discrimination between Arthur and Arkan wheats by image analysis. *Cereal Chemistry* 62:478-480.

Zayas, I., F.S. Lai, and Y. Pomeranz. 1986. Discrimination between wheat classes and varieties by image analysis. *Cereal Chemistry* 63:52-56.

Zayas, I., Y. Pomeranz, and F.S. Lai. 1989. Discrimination of wheat and non-wheat components in grain samples by image analysis. *Cereal Chemistry* 66:233-237.

Zayas, I., H. Converse, and J. Steele. 1990. Discrimination of whole from broken corn kernels with image analysis. *Transactions of the ASAE* 33:1642-1646.

APPENDIX A

Primary and Export Grade Determinants for CWRS wheat

(Source: Anonymous 1987)

RED SPRING WHEAT (Canada Western) - PRIMARY GRADE DETERMINANTS

	Standard of Quality				Maximum Limits of			
					Foreign Material		Wheats of Other Classes or Varieties	
Grade Name	Minimum Test Weight kg/hL	Variety	Minimum Hard Vitreous Kernels	Degree of Soundness	Matter Other Than Cereal Grains	Total Including Cereal Grains	Contrasting Classes	Total Including Contrasting Classes
No. 1 Canada Western Red Spring	75.0	Any variety of red spring wheat equal to Neepawa	65.0%	Reasonably well matured, reasonably free from damaged kernels	About 0.2%	0.75%	1.0%	3.0%
No. 2 Canada Western Red Spring	72.0	Any variety of red spring wheat equal to Neepawa	35.0%	Fairly well matured, may be moderately bleached or frost damaged, but reasonably free from severely damaged kernels	About 0.3%	1.5%	3.0%	6.0%
No. 3 Canada Western Red Spring	69.0	Any variety of red spring wheat equal to Neepawa	-	May be frost damaged, immature or weathered, but moderately free from severely damaged kernels	About 0.5%	3.5%	5.0%	10.0%
Canada Western Feed	No Minimum	Any type or variety of wheat excluding amber durum	No Minimum	Excluded from other grades of wheat on account of light weight or damaged kernels, but shall be reasonably sweet	1.0%	10.0%	No Limit 10.0% amber durum only	
Final Grade Name	Canada Western Feed		No. 3 C.W. Red Spring		Over 1.0% grade Wheat, Sample C.W. Account Admixture	Over 10.0% grade Mixed Grain, C.W. Wheat	Canada Western Feed Over 10.0% amber durum grade Wheat, Sample C.W. Account Admixture	

RED SPRING WHEAT - PRIMARY GRADE DETERMINANTS

Grade Name	Sprouted: Severe	Sprouted: Total Incl. Severe Sprouted	Binburnt Severe Mildew Rotted Mouldy	Heated Incl. Binburnt	Fireburnt	Stones	Ergot	Sclerotinia	Smudge	Total Smudge and Blackpoint
No. 1 C.W. Red Spring	0.1%	0.5%	2K	0.1%	Nil	3K	3K	3K	30K	10.0%
No. 2 C.W. Red Spring	-	1.5%	5K	0.75%	Nil	3K	6K	6K	1.0%	20.0%
No. 3 C.W. Red Spring	-	5.0%	10K	2.0%	Nil	6K	24K	24K	5.0%	35.0%
Canada Western Feed	No Limit		10.0%	10.0%	2.0%	10K	0.25%	0.25%	No Limit	No Limit
Final Grade Name	Canada Western Feed		Over 10.0% grade Wheat, Sample C.W. Account Heated		Over 2.0% grade Wheat, Sample C.W. Account Fireburnt	Over grade tolerance up to 2.5% grade Rejected "grade" Account Stones. Over 2.5% grade Wheat, Sample Salvage	Over 0.25% grade Wheat, Sample C.W. Account Ergot	Over 0.25% grade Wheat, Sample C.W. Account Admixture	Canada Western Feed	Canada Western Feed

Grade Name	Shrunken and Broken: Shrunken	Shrunken and Broken: Broken	Shrunken and Broken: Total	* Degermed	** Grass Green	Pink Kernels	Artificial Stain No Residue	Natural Stain	*** Insect Damage: Sawfly Midge	*** Insect Damage: Grasshopper Army Worm	Dark Immature
No. 1 C.W. Red Spring	6.0%	6.0%	7.0%	4.0%	0.75%	1.5%	Nil	0.5%	2.0%	1.0%	1.0%
No. 2 C.W. Red Spring	10.0%	10.0%	11.0%	7.0%	2.0%	5.0%	5K	2.0%	8.0%	3.0%	2.5%
No. 3 C.W. Red Spring	No Limit	15.0%	No Limit Providing Broken Tolerances Not Exceeded	13.0%	10.0%	10.0%	10K	5.0%	25.0%	8.0%	10.0%
Canada Western Feed	No Limit	50.0%		No Limit	No Limit	No Limit	2.0%	No Limit	No Limit	No Limit	No Limit
Final Grade Name	No. 3 C.W. Red Spring	Over 50.0% grade Sample Broken Grain		Canada Western Feed	Canada Western Feed	Canada Western Feed	Over 2.0% grade Wheat, Sample C.W. Account Stained Kernels	Canada Western Feed	Canada Western Feed	Canada Western Feed	Canada Western Feed

*Degermed: Tolerances apply to kernels not classed as sprouted.

**Grass Green Kernels: Tolerances are given as a general guide and may be increased or reduced in the judgment of the inspector after consideration of the overall quality of a sample.

***Insect Damage: Tolerances are not absolute maximums. Inspectors must consider the degree of damage in conjunction with the overall quality of the sample.

NOTE: THE LETTER "K" IN THESE TABLES REFERS TO KERNEL SIZE PIECES IN 500 GRAMS.

RED SPRING WHEAT - EXPORT GRADE DETERMINANTS

Grade Name	Commercial Cleanliness: Broken Grain Thru 5 Δ	Material through 4.5 R.H. and Roughage: SSDS	RHGE	ATT	TOT	Total Foreign Material: Seeds and Wild Oats: LSDS	SSDS	W.O.	TOT	RHGE	ATT	Stones	Total Mineral Matter	Ergot	Sclero-tinia	Other Cereal Grains	Total Foreign Material
No. 1 C.W. Red Spring	0.30%	0.05%	0.05%	0.10%	0.10%	0.20%	0.05%	0.05%	0.20%	0.05%	0.10%	0.03%	0.06%	0.01%	0.01%	0.40%	0.40%
No. 2 C.W. Red Spring	0.30%	0.05%	0.05%	0.10%	0.10%	0.20%	0.05%	0.05%	0.20%	0.05%	0.10%	0.03%	0.10%	0.02%	0.02%	0.75%	0.75%
No. 3 C.W. Red Spring	0.30%	0.05%	0.05%	0.10%	0.10%	0.20%	0.05%	0.05%	0.20%	0.05%	0.10%	0.06%	0.10%	0.04%	0.04%	1.25%	1.25%
Canada Western Feed	0.50%	0.05%	0.10%	0.10%	0.10%	0.50%	0.05%	0.10%	0.50%	0.10%	0.10%	0.10%	0.25%	0.10%	0.10%	5.0%	5.0%

Grade Name	Wheats of Other Classes: Contrasting Classes	Total Including Cont. Classes	Minimum Hard Vitreous Kernels	Sprouted: Severe	Total Including Severe Sprouted	Heated and Binburnt	Shrunken and Broken: Shrunken	Broken	Total
No. 1 C.W. Red Spring	0.30%	1.5%	65.0%	0.1%	0.5%	0.05% including 1 binburnt kernel per 1000 g	6.0%	5.0%	7.0%
No. 2 C.W. Red Spring	1.5%	3.0%	35.0%		1.5%	0.4% including 4 binburnt kernels per 1000 g	10.0%	8.0%	11.0%
No. 3 C.W. Red Spring	2.5%	5.0%	No Minimum		5.0%	1.0% including 6 binburnt kernels per 1000 g	No Limit	13.0%	No Limit providing broken tolerances not exceeded
Canada Western Feed	No Limit (10.0% Amber Durum only)		No Minimum	No Limit		2.5% including 2.5% binburnt kernels	No Limit	50.0%	

APPENDIX B

CLASSIFICATION ACCURACIES
WITH
SELECTED FEATURES

Table B1 Confusion matrix of the ten feature model with thirteen classes for the leave-one-out method (Normal estimation)

Class (to)→ (from)↓	CWRS	Durum	Barley	Rye	Oats	M-whead	Chaff	Wildoats	Canola	wbwheat	Flax	Broken	S-whead
CWRS wheat(3600)*	3598 (99.9+)	0	0	2 (0.1)	0	0	0	0	0	0	0	0	0
Durum (1200)	5 (0.4)	1161 (96.8)	7 (0.6)	27 (2.3)	0	0	0	0	0	0	0	0	0
Barley (1200)	0	10 (0.8)	1184 (98.7)	6 (0.5)	0	0	0	0	0	0	0	0	0
Rye (1200)	0	27 (2.3)	13 (1.1)	1160 (96.7)	0	0	0	0	0	0	0	0	0
Oats (1200)	0	0	0	0	1200 (100)	0	0	0	0	0	0	0	0
M -Whead (1200)	0	0	0	0	0	1183 (98.6)	0	0	0	0	0	0	17 (1.4)
Chaff (1200)	0	0	0	0	0	4 (0.3)	1088 (90.7)	0	0	0	0	36 (3.0)	72 (6.0)
Wildoats (1200)	0	0	0	0	0	0	0	1200 (100)	0	0	0	0	0
Canola (1200)	0	0	0	0	0	0	0	0	1198 (98.8)	2 (0.2)	0	0	0
W-bwheat (1200)	0	0	0	0	0	0	0	0	10 (0.8)	1188 (99.0)	1 (0.1)	1 (0.1)	0
Flax (1200)	0	0	0	0	0	0	0	0	0	0	1198 (98.8)	2 (0.2)	0
Broken (1200)	0	0	0	0	0	0	26 (2.2)	0	0	0	1 (0.1)	1173 (97.8)	0
S-Whead (1200)	0	0	0	0	0	20 (1.7)	15 (1.25)	0	0	0	0	0	1165 (97.1)

* Sample size, + Values expressed in percentage .

Table B2 Confusion matrix of the ten features model with thirteen classes for the hold-out method (Normal estimation)

Class (to)→ (from)↓	CWRS	Durum	Barley	Rye	Oats	M-whead	Chaff	Wildoats	Canola	wbwheat	Flax	Broken	S-whead
CWRS wheat(900)*	900 (100+)	0	0	0	0	0	0	0	0	0	0	0	0
Durum (300)	0	258 (86.0)	14 (4.6)	28 (9.3)	0	0	0	0	0	0	0	0	0
Barley (300)	0	10 (3.3)	288 (96.0)	2 (0.7)	0	0	0	0	0	0	0	0	0
Rye (300)	0	5 (1.7)	0	295 (98.3)	0	0	0	0	0	0	0	0	0
Oats (300)	0	0	0	0	300 (100)	0	0	0	0	0	0	0	0
M-Whead (300)	0	0	0	0	0	300 (100)	0	0	0	0	0	0	0
Chaff (300)	27 (9.0)	0	0	18 (6.0)	199 (66.3)	56 (18.7)	0	0	0	0	0	0	0
Wildoats (300)	0	0	0	0	0	0	10 (3.3)	275 (91.7)	0	0	0	0	15 (5.0)
Canola (300)	0	0	0	0	0	0	0	0	300 (100)	0	0	0	0
W-bwheat (300)	0	0	0	0	0	0	0	0	0	299 (99.7)	1 (0.3)	0	0
Flax (300)	0	0	0	0	0	0	0	0	0	0	300 (100)	0	0
Broken (300)	0	0	0	0	0	0	6 (2.0)	0	0	0	0	294 (98.0)	0
S-Whead (300)	0	0	0	0	0	6 (2.0)	6 (2.0)	0	0	0	0	0	292 (97.3)

* Sample size, + Values expressed in percentage

Table B3 Confusion matrix of the ten features model with thirteen classes for the leave-one-out method (Non-parametric estimation)

Class (to)→ (from)↓	CWRS	Durum	Barley	Rye	Oats	M-	Chaff	Wildoats	Canola	wbwheat	Flax	Broken	S-whead	Other
CWRS wheat(3600)	3600 (100+)	0	0	0	0	0	0	0	0	0	0	0	0	0
Durum (1200)	0	1176 (98.0)	8 (0.7)	16 (1.3)	0	0	0	0	0	0	0	0	0	0
Barley (1200)	0	28 (2.3)	1164 (97.0)	8 (0.7)	0	0	0	0	0	0	0	0	0	0
Rye (1200)	0	43 (3.6)	7 (0.6)	1150 (95.8)	0	0	0	0	0	0	0	0	0	0
Oats (1200)	0	0	0	0	1200 (100)	0	0	0	0	0	0	0	0	0
M-Whead (1200)	0	0	0	0	2 (0.2)	1186 (98.3)	1 (0.1)	0	0	0	0	0	11 (0.9)	0
Chaff (1200)	0	0	0	0	0	0	1126 (93.8)	0	0	0	0	26 (2.2)	48 (4.0)	0
Wildoats (1200)	0	0	0	0	0	0	0	1200 (100)	0	0	0	0	0	0
Canola (1200)	0	0	0	0	0	0	0	0	1197 (99.8)	3 (0.2)	0	0	0	0
w-bwheat (1200)	0	0	0	0	0	0	0	0	4 (0.3)	1196 (99.7)	0	0	0	0
Flax (1200)	0	0	0	0	0	0	0	0	0	0	1197 (99.8)	3 (0.2)	0	0
Broken (1200)	0	0	0	0	0	0	17 (1.4)	0	0	0	0	1183 (98.6)	0	0
S-Whead (1200)	0	0	0	0	0	14 (1.2)	22 (1.8)	0	0	0	0	0	1163 (96.8)	2 (0.2)

* Sample size, + Values expressed in percentage.

Table B4 Confusion matrix of the ten features model with thirteen classes for the hold-out method (Non-parametric estimation)

Class (to)→ (from)↓	CWRS	Durum	Barley	Rye	Oats	Mwhead	Chaff	Wildoats	Canola	wbwheat	Flax	Broken	S-whead	Other
CWRS wheat(900)*	900 (100+)	0	0	0	0	0	0	0	0	0	0	0	0	0
Durum (300)	0	282 (94.0)	5 (1.7)	10 (3.3)	0	0	0	0	0	0	0	0	0	3 (1.0)
Barley (300)	0	3 (1.0)	297 (99.0)	0	0	0	0	0	0	0	0	0	0	0
Rye (300)	0	6 (2.0)	0	294 (98.0)	0	0	0	0	0	0	0	0	0	0
Oats (300)	0	0	0	0	300 (100)	0	0	0	0	0	0	0	0	0
M-Whead (300)	0	0	0	0	0	300 (100)	0	0	0	0	0	0	0	0
Chaff (300)	46 (15.3)	0	0	0	237 (79.0)	6 (2.0)	11 (3.7)	0	0	0	0	0	0	0
Wildoats (300)	0	0	0	0	0	0	0	300 (100)	0	0	0	0	0	0
Canola (300)	0	0	0	0	0	0	0	0	300 (100)	0	0	0	0	0
W-bwheat (300)	0	0	0	0	0	0	0	0	0	300 (100)	0	0	0	0
Flax (300)	0	0	0	0	0	0	0	0	0	0	300 (100)	0	0	0
Broken (300)	0	0	0	0	0	0	4 (1.3)	0	0	0	0	296 (98.7)	0	0
S-Whead (300)	0	0	0	0	0	10 (3.3)	1 (0.3)	0	0	0	0	0	289 (96.3)	0

* Sample size, + Values expressed in percentage.

Table B5 Confusion matrix of the five features model with thirteen classes for the leave-one-out method (Normal estimation)

Class (to)→ (from)↓	CWRS	Durum	Barley	Rye	Oats	M-whead	Chaff	Wildoats	Canola	wbwheat	Flax	Broken	S-whead
CWRS wheat(3600)	3599 (99.9+)	0	0	0	0	0	0	0	0	0	0	0	0
Durum (1200)	3 (0.3)	1084 (90.3)	34 (2.8)	79 (6.6)	0	0	0	0	0	0	0	0	0
Barley (1200)	0	52 (4.3)	1137 (94.8)	11 (0.9)	0	0	0	0	0	0	0	0	0
Rye (1200)	0	111 (9.3)	25 (2.1)	1064 (88.6)	0	0	0	0	0	0	0	0	0
Oats (1200)	0	0	0	0	1199 (99.9)	1 (0.1)	0	0	0	0	0	0	0
M-Whead (1200)	0	0	0	0	1 (0.1)	1178 (98.2)	6 (0.5)	0	0	0	0	0	15 (1.3)
Chaff (1200)	0	0	0	0	0	1 (0.1)	1016 (84.7)	0	0	0	0	34 (2.8)	149 (12.4)
Wildoats (1200)	0	0	0	0	0	0	0	1200 (100)	0	0	0	0	0
Canola (1200)	0	0	0	0	0	0	0	0	1178 (98.2)	19 (1.6)	0	3 (0.3)	0
W-bwheat (1200)	0	0	0	0	0	0	0	0	21 (1.8)	1156 (96.3)	11 (0.9)	12 (1.0)	0
Flax (1200)	0	0	0	0	0	0	1 (0.1)	0	0	6 (0.5)	1181 (98.4)	12 (1.0)	0
Broken (1200)	0	0	0	0	0	0	68 (5.7)	0	4 (0.3)	0	81 (6.8)	1047 (87.3)	0
S-Whead (1200)	0	0	0	0	0	0	21 (1.75)	0	0	0	0	0	1169 (97.3)

* Sample size, + Values expressed in percentage.

Table B6 Confusion matrix of the five features model with thirteen classes for the leave-one-out method (Non-parametric estimation)

Class (to)→ (from)↓	CWRS	Durum	Barley	Rye	Oats	M whead	Chaff	Wildoats	Canola	wbwheat	Flax	Broken	S-whead	Other
CWRS wheat(3600)*	3600 (100+)	0	0	0	0	0	0	0	0	0	0	0	0	0
Durum (1200)	0	1084 (90.3)	34 (2.8)	75 (6.3)	0	0	0	0	0	0	0	0	0	7 (0.6)
Barley (1200)	0	48 (4.0)	1133 (94.4)	8 (0.7)	0	0	0	0	0	0	0	0	0	11 (0.9)
Rye (1200)	0	90 (7.50)	10 (0.8)	1092 (91.0)	0	0	0	0	0	0	0	0	0	8 (0.7)
Oats (1200)	0	0	0	0	1200 (100)	0	0	0	0	0	0	0	0	0
M-Whead (1200)	0	0	0	0	0	1188 (99.0)	0	0	0	0	0	0	12 (1.0)	0
Chaff (1200)	0	0	0	0	0	0	1112 (92.7)	0	0	0	0	31 (2.6)	56 (4.7)	1 (0.1)
Wildoats (1200)	0	0	0	0	0	0	0	1200 (100)	0	0	0	0	0	0
Canola (1200)	0	0	0	0	0	0	0	0	1194 (99.5)	6 (0.5)	0	0	0	0
w-bwheat (1200)	0	0	0	0	0	0	0	0	12 (1.0)	1175 (97.9)	7 (0.6)	5 (0.4)	0	1 (0.1)
Flax (1200)	0	0	0	0	0	0	0	0	0	5 (0.4)	1183 (98.6)	12 (1.0)	0	0
Broken (1200)	0	0	0	0	0	0	28 (2.3)	0	1 (0.1)	0	7 (0.6)	1163 (96.9)	0	1 (0.1)
S-Whead (1200)	0	0	0	0	0	8 (0.7)	37 (3.1)	0	0	0	0	0	1156 (96.3)	0

* Sample size, + Values expressed in percentage.

Table B7 Confusion matrix of the five features model with thirteen classes for the hold-out method (Normal estimation)

Class (to)→ (from)↓	CWRS	Durum	Barley	Rye	Oats	M whead	Chaff	Wildoats	Canola	wbwheat	Flax	Broken	S-whead
CWRS wheat(900)*	900 (100+)	0	0	0	0	0	0	0	0	0	0	0	0
Durum (300)	0	147 (49.0)	44 (14.7)	109 (36.3)	0	0	0	0	0	0	0	0	0
Barley (300)	0	22 (7.3)	262 (87.3)	16 (5.3)	0	0	0	0	0	0	0	0	0
Rye (300)	0	8 (2.67)	0	292 (97.3)	0	0	0	0	0	0	0	0	0
Oats (300)	0	0	0	0	300 (100)	0	0	0	0	0	0	0	0
M-Whead (300)	0	0	0	0	0	300 (100)	0	0	0	0	0	0	0
Chaff (300)	42 (14.0)	0	0	2 (0.7)	230 (76.7)	26 (8.7)	0	0	0	0	0	0	0
Wildoats (300)	0	0	0	0	0	0	119 (39.7)	177 (59.0)	0	0	0	0	4 (1.3)
Canola (300)	0	0	0	0	0	0	0	0	297 (99.0)	3 (1.0)	0	0	0
W-bwheat (300)	0	0	0	0	0	0	0	0	2 (0.7)	284 (94.7)	8 (2.7)	6 (2.0)	0
Flax (300)	0	0	0	0	0	0	0	0	0	5 (1.7)	293 (97.7)	2 (0.7)	0
Broken (300)	0	0	0	0	0	0	22 (7.3)	0	1 (0.3)	0	0	277 (92.3)	0
S-Whead (300)	0	0	0	0	0	6 (2.0)	3 (1.0)	0	0	0	0	0	291 (97.0)

* Sample size, + Values expressed in percentage.

Table B8 Confusion matrix of the five features model with thirteen classes for the hold-out method (Non-parametric estimation)

Class (to)→ (from)↓	CWRS	Durum	Barley	Rye	Oats	M whead	Chaff	Wildoats	Canola	wbwheat	Flax	Broken	S-whead	Other
CWRS wheat(900)*	900 (100+)	0	0	0	0	0	0	0	0	0	0	0	0	0
Durum (300)	0	180 (60.0)	32 (10.7)	75 (25.0)	0	0	0	0	0	0	0	0	0	13 (4.3)
Barley (300)	0	13 (4.33)	286 (95.3)	0	0	0	0	0	0	0	0	0	0	1 (0.3)
Rye (300)	0	7 (2.3)	0	293 (97.7)	0	0	0	0	0	0	0	0	0	0
Oats (300)	0	0	0	0	300 (100)	0	0	0	0	0	0	0	0	0
M-Whead (300)	0	0	0	0	0	300 (100)	0	0	0	0	0	0	0	0
Chaff (300)	51 (17.0)	0	0	0	244 (81.3)	3 (1.0)	2 (0.7)	0	0	0	0	0	0	0
Wildoats (300)	0	0	0	0	0	0	0	300 (100)	0	0	0	0	0	0
Canola (300)	0	0	0	0	0	0	0	0	299 (99.7)	1 (0.3)	0	0	0	0
W-bwheat (300)	0	0	0	0	0	0	0	0	0	293 (97.7)	5 (1.7)	2 (0.7)	0	0
Flax (300)	0	0	0	0	0	0	0	0	0	4 (1.3)	292 (97.3)	4 (1.3)	0	0
Broken (300)	0	0	0	0	0	0	0	0	0	0	0	291 (97.0)	0	0
S-Whead (300)	0	0	0	0	0	8 (2.7)	13 (4.3)	0	0	0	0	0	279 (93.0)	0

* Sample size, + Values expressed in percentage.

Table B9 Confusion matrix of the 15 features model with thirteen classes for the leave-one-out method (Normal estimation)

Class (to)→ (from)↓	CWRS	Durum	Barley	Rye	Oats	M whead	Chaff	Wildoats	Canola	wbwheat	Flax	Broken	S-whead
CWRS wheat(3600)	3591 (99.8+)	0	0	9 (0.2)	0	0	0	0	0	0	0	0	0
Durum (1200)	7 (0.6)	1144 (95.3)	10 (0.8)	39 (3.3)	0	0	0	0	0	0	0	0	0
Barley (1200)	0	14 (1.2)	1173 (97.8)	13 (1.1)	0	0	0	0	0	0	0	0	0
Rye (1200)	1 (0.1)	25 (2.1)	13 (1.1)	1161 (96.8)	0	0	0	0	0	0	0	0	0
Oats (1200)	0	0	0	0	1200 (100)	0	0	0	0	0	0	0	0
M -Whead (1200)	0	0	0	0	0	1191 (99.3)	0	0	0	0	0	0	9 (0.8)
Chaff (1200)	0	0	0	0	0	4 (0.3)	1079 (89.9)	0	0	0	0	48 (4.0)	69 (5.8)
Wildoats (1200)	0	0	0	0	0	0	1 (0.1)	1199 (99.9)	0	0	0	0	0
Canola (1200)	0	0	0	0	0	0	2 (0.2)	0	1192 (99.3)	4 (0.3)	0	2 (0.2)	0
W-bwheat (1200)	0	0	0	0	0	0	1 (0.1)	0	10 (0.8)	1185 (98.8)	2 (0.2)	2 (0.2)	0
Flax (1200)	0	0	0	0	0	0	1 (0.1)	0	0	0	1195 (99.6)	4 (0.3)	0
Broken (1200)	0	0	0	0	0	0	27 (2.3)	0	3 (0.25)	0	5 (0.4)	1165 (97.1)	0
S-Whead (1200)	0	0	0	0	0	20 (1.7)	19 (1.6)	0	0	0	0	0	1162 (96.7)

* Sample size, + Values expressed in percentage.

Table B10 Confusion matrix of the 15 features model with thirteen classes for the leave-one-out method (Non-parametric estimation)

Class (to)→ (from)↓	CWRS	Durum	Barley	Rye	Oats	M whead	Chaff	Wildoats	Canola	wbwheat	Flax	Broken	S-whead	Other
CWRS wheat(3600)*	3600 (100+)	0	0	0	0	0	0	0	0	0	0	0	0	0
Durum (1200)	0	1189 (99.1)	2 (0.2)	8 (0.7)	0	0	0	0	0	0	0	0	0	1 (0.1)
Barley (1200)	0	14 (1.2)	1184 (98.7)	1 (0.1)	0	0	0	0	0	0	0	0	0	1 (0.1)
Rye (1200)	0	20 (1.7)	2 (0.2)	1176 (98.0)	0	0	0	0	0	0	0	0	0	2 (0.2)
Oats (1200)	0	0	0	0	1200 (100)	0	0	0	0	0	0	0	0	0
M-Whead (1200)	0	0	0	0	2 (0.2)	1190 (99.2)	0	0	0	0	0	0	8 (0.7)	0
Chaff (1200)	0	0	0	0	0	0	1167 (97.3)	0	0	0	0	13 (1.1)	20 (1.7)	0
Wildoats (1200)	0	0	0	0	0	0	1 (0.1)	1199 (99.9)	0	0	0	0	0	0
Canola (1200)	0	0	0	0	0	0	0	0	1198 (99.8)	2 (0.2)	0	0	0	0
w-bwheat (1200)	0	0	0	0	0	0	0	0	2 (0.2)	1197 (99.8)	0	1 (0.1)	0	0
Flax (1200)	0	0	0	0	0	0	0	0	0		1197 (99.8)	3 (0.2)	0	0
Broken (1200)	0	0	0	0	0	0	11 (0.9)	0	0	0	0	1187 (98.9)	0	2 (0.2)
S-Whead (1200)	0	0	0	0	0	7 (0.6)	7 (0.6)	0	0	0	0	0	1187 (98.9)	0

* Sample size, + Values expressed in percentage.

Table B11 Confusion matrix of the 15 features model with thirteen classes for the hold-out method (Normal estimation)

Class (to)→ (from)↓	CWRS	Durum	Barley	Rye	Oats	M whead	Chaff	Wildoats	Canola	wbwheat	Flax	Broken	S-whead
CWRS wheat(900)*	900 (100+)	0	0	0	0	0	0	0	0	0	0	0	0
Durum (300)	0	260 (86.7)	15 (5.0)	25 (8.3)	0	0	0	0	0	0	0	0	0
Barley (300)	0	10 (3.3)	288 (96.0)	2 (0.7)	0	0	0	0	0	0	0	0	0
Rye (300)	1 (0.3)	1 (0.3)	0	298 (99.3)	0	0	0	0	0	0	0	0	0
Oats (300)	0	0	0	0	300 (100)	0	0	0	0	0	0	0	0
M-Whead (300)	0	0	0	0	0	300 (100)	0	0	0	0	0	0	0
Chaff (300)	8 (2.7)	0	0	36 (12.0)	152 (50.7)	83 (27.7)	21 (7.0)	0	0	0	0	0	0
Wildoats (300)	0	0	0	0	0	0	11 (3.7)	286 (95.3)	0	0	0	0	3 (1.0)
Canola (300)	0	0	0	0	0	0	0	0	300 (100)	0	0	0	0
W-bwheat (300)	0	0	0	0	0	0	0	0	0	298 (99.3)	2 (0.7)	0	0
Flax (300)	0	0	0	0	0	0	0	0	0	0	299 (99.7)	1 (0.3)	0
Broken (300)	0	0	0	0	0	0	5 (1.7)	0	1 (0.3)	0	0	294 (98.0)	0
S-Whead (300)	0	0	0	0	0	10 (3.3)	3 (1.0)	0	0	0	0	0	287 (95.7)

* Sample size, + Values expressed in percentage.

Table B12 Confusion matrix of the 15 features model with thirteen classes for the hold-out method (Non-parametric estimation)

Class (to)→ (from)↓	CWRS	Durum	Barley	Rye	Oats	M wheat	Chaff	Wildoats	Canola	wbwheat	Flax	Broken	S-wheat	Other
CWRS wheat(900)*	900 (100+)	0	0	0	0	0	0	0	0	0	0	0	0	0
Durum (300)	0	285 (95.0)	5 (1.7)	7 (2.3)	0	0	0	0	0	0	0	0	0	3 (1.0)
Barley (300)	0	3 (1.0)	297 (99.0)	0	0	0	0	0	0	0	0	0	0	0
Rye (300)	0	2 (0.7)	0	298 (99.3)	0	0	0	0	0	0	0	0	0	0
Oats (300)	0	0	0	0	300 (100)	0	0	0	0	0	0	0	0	0
M-Whead (300)	0	0	0	0	0	300 (100)	0	0	0	0	0	0	0	0
Chaff (300)	18 (6.0)	0	0	0	228 (76.0)	4 (1.3)	49 (16.3)	0	0	0	0	0	0	1 (0.3)
Wildoats (300)	0	0	0	0	0	0	0	300 (100)	0	0	0	0	0	0
Canola (300)	0	0	0	0	0	0	0	0	300 (100)	0	0	0	0	0
W-bwheat (300)	0	0	0	0	0	0	0	0	0	300 (100)	0	0	0	0
Flax (300)	0	0	0	0	0	0	0	0	0	0	300 (100)	0	0	0
Broken (300)	0	0	0	0	0	0	0	0	0	0	0	297 (99.0)	0	0
S-Whead (300)	0	0	0	0	0	8 (2.7)	3 (1.0)	0	0	0	0	0	289 (96.3)	0

* Sample size, + Values expressed in percentage.

APPENDIX C

BETWEEN-CLASS CORRELATION COEFFICIENT MATRICES

Table C1 Between-class correlation coefficient matrix of morphological and basic color features

Between-Class Correlation Coefficients															
Feature↓→	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15
F1	1.00														
F2	0.97	1.00													
F3	0.93	0.98	1.00												
F4	0.94	0.85	0.77	1.00											
F5	0.93	0.84	0.76	0.99	1.00										
F6	0.94	0.84	0.75	0.99	0.98	1.00									
F7	0.91	0.82	0.76	0.98	0.99	0.96	1.00								
F8	0.95	0.99	0.99	0.80	0.79	0.78	0.77	1.00							
F9	0.96	0.99	0.99	0.84	0.83	0.82	0.83	0.99	1.00						
F10	0.95	0.98	0.98	0.84	0.84	0.81	0.84	0.98	0.99	1.00					
F11	0.84	0.94	0.96	0.65	0.63	0.63	0.62	0.96	0.94	0.92	1.00				
F12	0.93	0.92	0.89	0.84	0.83	0.84	0.82	0.91	0.92	0.92	0.78	1.00			
F13	0.88	0.91	0.92	0.71	0.70	0.71	0.70	0.93	0.92	0.62	0.42	0.61	1.00		
F14	0.79	0.71	0.59	0.81	0.75	0.85	0.69	0.65	0.64	0.06	0.04	0.06	0.05	1.00	
F15	0.45	0.62	0.73	0.16	0.15	0.12	0.16	0.70	0.65	0.60	0.74	0.33	0.66	0.08	1.00

C1 Between-class correlation coefficient matrix of morphological and basic color features (Cont.)

Between-Class Correlation Coefficients															
Feature	F16	F17	F18	F19	F20	F21	F22	F23	F24	F25	F26	F27	F28	F29	F30
F1	0.31	0.67	0.89	-0.41	0.59	0.50	0.18	-0.17	-0.25	-0.15	0.45	0.32	0.24	0.16	0.24
F2	0.49	0.85	0.88	-0.49	0.62	0.54	0.23	-0.16	-0.26	-0.15	0.49	0.54	0.45	0.25	0.32
F3	0.52	0.86	0.81	-0.54	0.61	0.54	0.21	-0.16	-0.26	-0.14	0.49	0.66	0.57	0.25	0.30
F4	0.11	0.46	0.87	-0.39	0.58	0.45	0.15	-0.20	-0.25	-0.16	0.41	0.01	-0.06	0.10	0.18
F5	0.00	0.38	0.84	-0.39	0.55	0.39	0.10	-0.18	-0.22	-0.13	0.35	-0.01	-0.09	0.06	0.11
F6	0.06	0.36	0.86	-0.32	0.51	0.31	0.09	-0.10	-0.14	-0.08	0.29	0.00	-0.06	0.09	0.15
F7	-0.07	0.33	0.80	-0.41	0.54	0.38	0.07	-0.18	-0.22	-0.13	0.34	-0.02	-0.09	0.03	0.05
F8	0.51	0.86	0.84	-0.51	0.62	0.54	0.22	-0.16	-0.26	-0.14	0.49	0.62	0.58	0.70	0.64
F9	0.44	0.80	0.84	-0.54	0.63	0.54	0.20	-0.18	-0.28	-0.15	0.49	0.55	0.53	0.65	0.59
F10	0.43	0.78	0.82	-0.55	0.64	0.54	0.17	-0.18	-0.28	-0.15	-0.48	0.54	0.51	0.61	0.54
F11	0.56	0.83	0.79	-0.50	0.58	0.49	0.26	-0.12	-0.22	-0.11	0.46	0.71	0.64	0.29	0.33
F12	0.29	0.55	0.76	-0.47	0.62	0.39	0.08	-0.15	-0.21	-0.13	0.33	0.30	0.23	0.17	0.24
F13	0.37	0.57	0.71	-0.45	0.56	0.34	0.08	-0.11	-0.18	-0.10	0.29	0.44	0.38	0.23	0.26
F14	0.00	0.05	0.80	-0.14	0.37	0.03	0.01	0.00	-0.00	-0.00	0.02	0.00	-0.00	0.00	0.02
F15	0.67	0.77	0.34	-0.53	0.37	0.34	0.16	-0.07	-0.18	-0.06	0.30	0.97	0.94	0.25	0.23

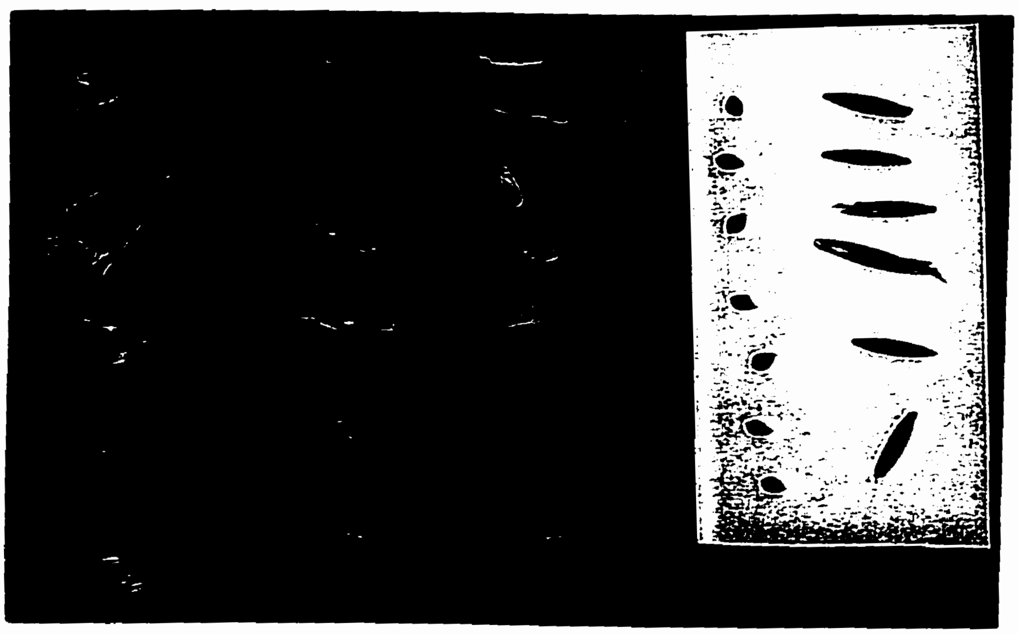
C1 Between-class correlation coefficient matrix of morphological and basic color features (cont.)

	Between-Class Correlation Coefficients														
Feature↓→	F16	F17	F18	F19	F20	F21	F22	F23	F24	F25	F26	F27	F28	F29	F30
F16	1.00														
F17	0.70	1.00													
F18	0.35	0.69	1.00												
F19	-0.30	-0.38	-0.46	1.00											
F20	0.28	0.46	0.66	-0.53	1.00										
F21	0.32	0.50	0.51	0.99	-0.40	1.00									
F22	0.21	0.30	0.31	-0.11	0.48	0.56	1.00								
F23	-0.07	-0.09	-0.13	0.34	-0.42	-0.39	-0.17	1.00							
F24	-0.15	-0.20	-0.21	0.42	-0.53	-0.53	-0.25	0.93	1.00						
F25	-0.09	-0.12	-0.16	0.24	-0.38	-0.40	-0.12	0.57	0.65	1.00					
F26	0.31	0.47	0.49	-0.36	0.92	0.95	0.77	-0.37	-0.49	-0.34	1.00				
F27	0.72	0.79	0.27	-0.38	0.30	0.34	0.19	-0.05	-0.16	-0.06	0.31	1.00			
F28	0.93	0.78	0.24	-0.38	0.26	0.33	0.30	-0.08	-0.22	-0.12	0.32	0.99	1.00		
F29	0.75	0.82	0.78	-0.27	0.64	0.72	0.82	-0.30	-0.38	-0.45	0.76	0.57	0.52	1.00	
F30	0.66	0.75	0.78	-0.24	0.63	0.71	0.85	-0.41	-0.45	-0.53	0.77	0.44	0.39	0.96	1.00

Note : F1-Area, F2-Perimeter, F3-Length, F4-Width, F5-Length of principal axis, F6-Length of minor axis, F7-Minimum Radius, F8-Maximum Radius, F9-std of radii , F10-First Fourier magnitude, F11-Second Fourier magnitude, F12-Third Fourier magnitude, F13-Fourth Fourier magnitude, F14-Aspect ratio, F15-Rectangular ratio, F16-Radius ratio, F17-Thinness Ratio, F18-Area Ratio, F19-Haralick ratio, F20-Avg R, F21-Avg-G, F22-Avg B, F23-std of R, F24-std of G, F25-std of B, F26-Intensity, F27-First invariant moment, F28-Second invariant moment, F29-Third invariant moment, and F30-Fourth invariant moment.

APPENDIX D

SAMPLES OF DOCKAGE CLASSES



1 2 3 4 5 6

1-multiple wheathead, 2-single wheathead, 3-chaff,
4-broken-wheat, 5- wild buckwheat, 6-wildoats.

Fig. D1 Samples of dockage classes