WHEAT CLASSIFICATION USING IMAGE ANALYSIS AND CRUSH-FORCE PARAMETERS

I. Y. Zayas, C. R. Martin, J. L. Steele, A. Katsevich

ABSTRACT. *A study was conducted to develop methodology for wheat classes and variety identification by combination of image analysis techniques with wheat hardness physical measurements. Wheat kernel morphometrical parameters were extracted from digitized images and hardness parameters were obtained from force-deformation curves from a single kernel wheat characterization system which also provided a kernel weight. Pattern recognition methods were applied to the data base of combined parameters for wheat kernels of six classes and seventeen varieties of soft and hard wheat. Recognition rates for parameter combinations of shape, size, and hardness scores were higher than hardness or imaging alone or when combined with weight. Hard and soft recognition rates of 94% was achieved with shape and hardness of the wheat kernels. A PC version of the developed algorithm was written and tested with the same data set. Satisfactory performance in the PC version confirmed the practicality of the method developed.* ***Keywords.*** *Wheat, Digital imaging, Machine vision, Pattern recognition, Multivariate analysis, Hardness.*

Grain quality attributes, determined by hardness, are very important for all end users and especially the milling and baking industries. The interim procedure implemented in 1987 by the Federal Grain Inspection Service (FGIS) for wheat classification is based on subjective human judgement. This current visual classification procedure is demanding, even for trained inspectors, because a wide variation in visual characteristics is caused by contrasting class, varietal, and environmental effects. Objective procedures for class or varietal identification based on chemistry or electrophoresis are successful in the laboratory but difficult to implement in the field-grading locations. Computerized measurement of physical characteristics of wheat could become the foundation for developing new objective wheat classification methods.

Computerized image analysis for wheat classification evolved from several studies. It is an attractive, nondestructive method, showing some potential for wheat inspection. Identification of wheat varieties and classes by morphometrical features (shape and size) was studied by Zayas et al. (1985, 1986, 1988), Newman et al. (1987), Symons and Fulcher (1988), Keefe and Draper (1986), Myers and Edsall (1989), and Thomson and Pomeranz (1991). These studies demonstrated the possibility of pairwise varietal identification with high recognition rates. Classwise correct identification was inconclusive and varied widely with the methodology used.

Article has been reviewed and approved for publication by the Food and Process Engineering Inst. of ASAE.

The authors are **Inna Y. Zayas,** ***ASAE Member Engineer***, Electronic Engineer, **Charles R. Martin,** ***ASAE Member***, Agricultural Engineer, Transport, **James L. Steele,** ***ASAE Member Engineer***, Agricultural Engineer, USDA-ARS, Grain Marketing Research and Production Center, Manhattan, Kansas; and **A. Katsevich**, Assistant Professor, University of Central Florida, Dept. of Mathematics, Orlando, Florida. **Corresponding author:** Inna Y. Zayas, USDA-GMPRC, 1515 College Ave., Manhattan, KS 66502; telephone: (913) 776-2758; fax: (913) 776- 2792; e-mail: <iz@unix.ksu.edu>.

A hardness instrument was developed by the United States Grain Marketing Research Laboratory (USGMRL) to classify wheat, based on crush-force features. The use of features extracted by digital image analysis in combination with crush-force features represents an extended range of wheat characterization. The combined feature vector covers the full scale of physical hardness and appearance of the wheat kernel. A combination of wheat morphometry and hardness features was used in a preliminary study of two contrasting classes, Caldwell Soft Red Winter Wheat (SRW) and Newton Hard Winter Wheat (HRW), by Zayas and Martin (1988) with encouraging results. A definite improvement of recognition rate was achieved when morphometry and hardness were combined. A fast nondestructive technique of digital image analysis included extracting morphometrical features for wheat classification and incorporated wheat hardness values in the feature vector for subsequent pattern recognition analysis provides new potential for wheat identification.

The objectives of this investigation were: (1) to identify hard versus soft wheats using combined features extracted from digital images and crush-force hardness features; and (2) to test the transportability of the developed algorithm to a personal computer (PC) environment.

MATERIAL AND METHODS

Seventeen wheat varieties from six classes were provided by FGIS. A randomly selected sample of 320 kernels per variety was studied (table 1). A flowchart of experiments is shown on figure 1. Images of each wheat kernel were acquired in two positions: kernel crease down and kernel profile. The wheat kernels were crushed by a hardness instrument whose data base included previous kernel weight registration. The crushed material was collected for subsequent image analysis, which is described elsewhere (Zayas et al., 1991). Thus images of individual kernels were acquired before crushing and images of collected material after crushing.

Table 1. Wheat varieties and classes

No.	Variety	Class
1	TAM105	HRW
2	CENTURK	HRW
3	BENNETT	HRW
4	NEWTON	HRW
5	DODGE	HRW
6	MARSHAL	HRS
7	YECORO	HRS
8	BUTTE	HRS
9	LEN	HRS
10	TELEMARK	HRS
11	CALDWELL	SRW
12	TITAN	SRW
13	NUGAIN	SWW
14	STEPHEN	SWW
15	TRES	CLUB
16	CANDO	DU
17	MONROE	DU

HRW - Hard Red Winter Wheat.
HRS - Hard Red Spring Wheat.
SRW - Soft Red Winter Wheat.
SWW - Soft White Winter Wheat.
DU - Durum.

EQUIPMENT

A commercial Kontron Image Processing System (IPS) with SUN 3/160C as host computer was used for image acquisition and analysis. The SUN work station with Unix operating system had 8Mb RAM memory and a 1068Mb disk storage. The processor MC68020 speed was 16.67 MHz. A KONTRON stand-alone system with a microprogrammable 10 mips pipeline array processor was independent of the host computer. An analog to digital converter (20 MHz) had a grey tone resolution of 8 bits (256 grey levels). Acquired and preprocessed images were transferred to the SUN 3/160C through a 16-bit interface, stored, and analyzed there. The power supplied to the computer and illumination lamps was controlled by a Solatron line regulator. The output power was conditioned to 110 v with 0.25% precision.

Statistical data analysis was done using a SUN 4/60 SPARC-1 workstation. The same data analysis was performed using DELL 310 PC with an Intel 80386 chip, 20-MHz processor speed, MS DOS system, 2 MB RAM memory, 640 KB available for programming, and a 100 MB hard disk.

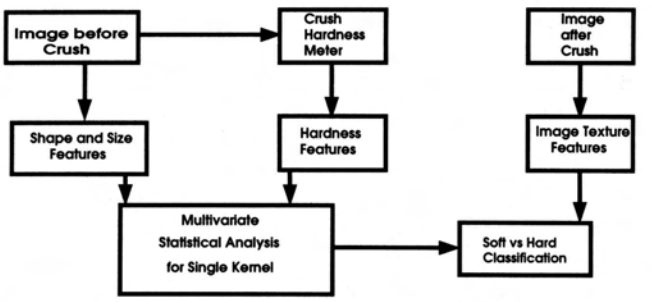

Figure 1–Flowchart for identification of hard and soft wheat kernels by digital imaging features and crush hardness scores.

IMAGE ACQUISITION

Four quartz halogen lamps (250W) provided illumination for the wheat. Kernels were positioned on a metal tray 240 × 160 mm, covered by black sticky tape. Calibration of measurements (mm) was performed for each tray with four polyester spheres. Repeatability of these values indicated the system and the illumination unit performance.

Images were captured via a monochrome DAGE-MTI 81 camera, which is a high-resolution 1600 line camera with a Newvicon tube, interfaced with a Kontron IPS. A Nikkor lens, with f = 2.8 was attached to the camera. The magnification of the resulting image was 1 pixel = 0.0175 mm. In-house software was designed to correct the aspect ratio 1:1.2 of a pixel and variability of measurements due to other factors. Wheat kernels were arranged on a tray in 10 rows of 32 kernels. The tray had mobility in two orthogonal directions. For the first run all kernels were positioned crease down. Images of the wheat kernels were acquired with one kernel per field of view. Then wheat kernels were rearranged in profile position and images were acquired again. Images were digitized and stored in 612 × 480 × 8 bit format. Kontron software was used for feature extraction. Morphometrical features (area, perimeter, length and width) were extracted and stored for future data analysis.

HARDNESS VALUES

Hardness values were acquired by a single-kernel wheat characterization instrument described by Martin et al. (1993). Weight of each kernel was measured with an analytical balance and stored in a database before processing. A crushing device was used to determine crush force, moisture, and size characteristics. Single wheat kernels were crushed as they passed through a wedge-shaped cavity between a smooth crescent surface and a coarse-toothed rotor. The crescent was a lever supported by a load cell that measured a force vector from the crushing action. The rotor was insulated electrically so that conductivity measurements could be obtained during kernel contact between the rotor and crescent. The conductivity data were used to determine kernel moisture. Kernel size was taken into consideration using the time that a kernel exerted force on the crescent. Hardness of single kernels was corrected for the effects of kernel moisture and size on the crush force profile. Data acquisition was automatic and controlled by computer software that responded to the force and conductance data from an analog to digital converter. Some observations were lost during crushing because of inconsistent force-deformation data collection. Therefore the numbers of kernels in a final set submitted for analysis varied.

RESULTS AND DISCUSSION

Morphometrical features extracted from binary images were position invariant. Several shape features were derived from basic features of crease down projection and profile projection images of wheat kernels (table 2). New combined features from two projections were computed. Data files carrying wheat kernel morphometrical information were merged with data files carrying hardness values. For each wheat kernel, feature vector components

Table 2. Wheat kernel morphometrical and hardness features

No.	Feature	Description
1.	z2	weight
		POSITION : DOWN
2.	z3	AREA_d*
3.	z4	DMAX_d†
4.	z5	DMIN_d‡
5.	z6	CPER_d§
6.	z7	PER_dll
		POSITION : PROFILE
7.	z8	AREA_p
8.	z9	DMAX_p
9.	z10	DMIN_p
10.	z11	CPER_p
11.	z12	PER_p
		DERIVED FROM BASIC FEATURES
12.	r	difference of rectangularities r = r1 – r2
13.	r1	rectangularity_d [AREA/(DMAX*DMIN)]
14.	r2	rectangularity_p [AREA/(DMAX*DMIN)]
15.	e	difference of eq. diameters [2*√(AREA/Π)]
16.	e1	eq. diameter_d
17.	e2	eq. diameter_p
18.	s	CSF-circularity shape factor difference [(Per²/4Π*AREA)]
19.	s1	CSF_d (circularity shape factor)
20.	s2	CSF_p (circularity shape factor)
21.	p	aspect ratio difference (DMAX/DMIN) of two positions
22.	p1	aspect difference_d (DMAX/DMIN)
23.	p2	aspect difference_p (DMAX/DMIN)
24.	a	area difference of two positions
25.	b	rectangularity ratio of 'down'/'profile'
26.	c	circularity shape factor ratio of 'down'/'profile'
27.	d	eq. diameter ratio of 'down'/'profile'
		HARDNESS FEATURES#
28.	c2	sum of 1/DY for all DY > 0, 1/(A/D count)**
29.	c3	sum of DY for all DY > 0, A/D count††
30.	c4	number of DY > 8‡‡
31.	c5	sum of DY greater than 0 and less than or equal to 8
32.	c6	peak force, A/D count§§
33.	c7	total number of DY
34.	c8	number of DY > 0llll

* AREA - area of the kernel.
† DMAX - maximum length among 32 Feret diameters.
‡ DMIN - minimum length among 32 Feret diameters.
§ CPER - convex perimeter.
ll PER - perimeter.
Hardness features - detailed description of hardness features(c2-c8) is given in Martin et al., 1993.
** A parameter proportional to hardness, large for soft wheat kernels, small for hard kernels.
†† A parameter related to the work required to crush a kernel.
‡‡ A parameter proportional to hardness.
§§ Used to select data points for single kernel moisture measurement.
llll A parameter related to size based on the time a kernel exerts force on the crescent.

collectively contained information on kernel appearance and hardness qualities as shown in table 2.

The data set of feature vectors for 17 varieties and six classes of wheat was subdivided into hard and soft subclasses. In this study, the goal of the pattern recognition algorithm was to classify wheat kernels into one of two categories: hard or soft. The database described provided a set of wheat kernel feature vectors for each category. Randomly selected half of the set of known feature vectors was used to derive a classification algorithm. These observations, feature vectors describing morphometry and hardness of individual kernels, comprised the training set. The remaining observations were considered as unknown categories and comprised the test data set. The level of algorithm performance was evaluated by correct classification rate. To achieve better performance, either the member of feature vectors or an alternative classification algorithm would be needed.

Statistical Data Analysis

For the first stage, SAS (Statistical Analysis Systems Institute, 1991) was used for data analysis. The best performing subset of features from all 34 available was selected using stepwise analysis. The corresponding R^2 (SAS, Procedure STEPDISK) are shown in table 3.

Wheat kernel observations were split into two data sets: "training" and "test". The training data set of 150 observations was taken out from the whole data set for each variety (approximately 300 observations) using SAS provision for random sampling. The remaining observations comprised the test data. To compute discriminant functions for the two-group classification of hard versus soft, the training set of data was used to compute linear or quadratic discriminant functions (SAS, Procedure DISCRIM). Covariance matrices, mean vectors, and probabilities of membership for each observation were computed. A test data set of unknown observations was classified with the computed algorithm for the training set, and the results are shown in table 4.

The discriminant power of wheat kernel morphometry, crush hardness parameters, and weight were compared. Different models were evaluated using different feature vector components as an input for computing discriminant functions. Use of only force-deformation features resulted in correct classification of 79% for hard wheats and 93% for soft wheats for training and test data sets. No significant improvement was noticed when weight was used with the crush parameters. The correct classification rates for training and test data were about 80% for hard wheats and 93% for soft wheats. The classification rate was worse when only

Table 3. Features selected by procedure STEPDISK

No.	Variable	Average Squared Canonical Correlation R^2
1	c2	0.4585
2	c4	0.4975
3	e1	0.6216
4	c5	0.6275
5	z10	0.6354
6	z6	0.6399
7	s1	0.6518
8	c6	0.6585
9	z12	0.6614
10	p	0.6635
11	z4	0.6641
12	c7	0.6647
13	z2	0.6653
14	z11	0.6661
15	a	0.6676
16	s	0.6704
17	c	0.6714
18	c3	0.6719
19	p2	0.6721
20	r2	0.6729

Table 4. Correct recognition rates of hard (ha) and soft (so) wheat kernel discrimination using image, crush deformation features, and weight for training and test data sets

Training Data Set (%)										
FEATURES	Crush *1		Crush and Weight *2		Image *3		Crush Image and Weight *4		Crush Image *5	
TYPE	ha	so	ha	so	ha	so	ha	so	ha	so
Hard	79.3	20.6	79.7	20.2	62.6	37.3	94.5	5.5	94.5	5.5
Soft	6.5	93.4	6.5	93.4	9.0	90.9	4.4	95.6	5.3	94.7
Test Data Set (%)										
FEATURES	Crush *1		Crush and Weight *2		Image *3		Crush Image and Weight *4		Crush Image *5	
TYPE	ha	so	ha	so	ha	so	ha	so	ha	so
Hard	79.8	20.1	80.3	19.6	60.3	39.6	93.3	6.7	93.2	6.7
Soft	6.7	93.2	6.7	93.2	8.6	91.3	5.0	94.9	5.3	94.7

* 1: c2 c3 c4 c5 c6 c7 c8
* 2: c2 c3 c4 c5 c6 c7 c8 z2
* 3: z3-z12 r1 r2 r e1 e2 e s1 s2 s p1 p2 p a b c d
* 4: c2 c4 e1 z1 c5 z4 s1 c6 z12 z6 e1 p z11 a s2 c z2
* 5: c2 c4 e1 c5 z4 c6 z12 z6 e1 p z11 a s2 c z2 r2 b r1

image features were used. The correct classification results dropped to 63% for hard wheats and 91% for soft wheats. The combination of image features and force-deformation features gave excellent recognition rates of about 94% for hard wheats and 95% for soft wheats for training and test data sets. Results for training and test data did not differ significantly: 94.5% correct recognition for training hard data set and 93.2% for test hard data set. Including kernel weight did not significantly algorithm performance. The combination of image features, force-deformation, and weight resulted in 94% correct recognition for hard wheats and 95% for soft wheats.

Canonical discriminant analysis was performed using the full set of observations (approximately 300 per variety) to get a graphical illustration of discrimination. Two canonical functions were computed out of 34 feature components to reduce the multidimensional space to two-dimensional space. SAS CANDISC was used for graphic presentation and for comparison of recognition rate as well. Figure 2 illustrates good clustering for hard and soft wheats with some overlap when values of canonical coefficients can1 and can2 were plotted. For details on the use of SAS Procedures DISCRIM, STEPDISK and CANDISC, see Zayas et al., 1990.

Personal Computer (PC) Implementation of Data Analysis

Obvious questions were raised as to the practicality of the classification results achieved with methodology described. Utilization of the developed methodology in a real-life situation depends on the affordability of the equipment used. The study was extended to explore the possibility of transferring the algorithm described above to a PC. A PC version of the data analysis algorithm was developed to resolve transferability. The programs were designed to be flexible and easy to use with input in a dialogue mode and used as a stand alone program to

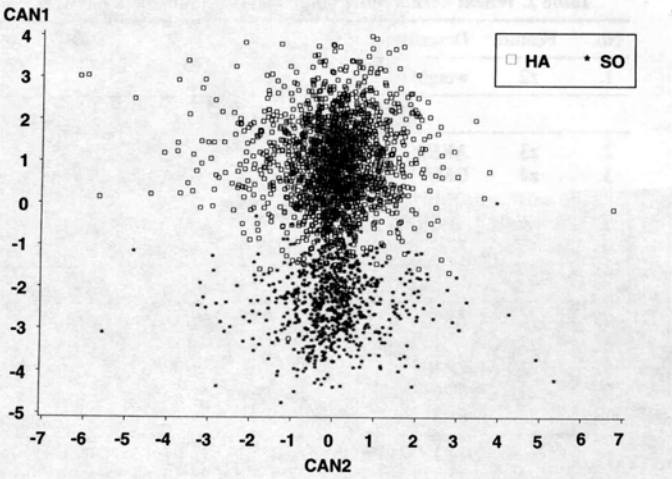

Figure 2–Plot of canonical functions distinguishing hard and soft wheat kernels by shape, size, and hardness as input features.

perform canonical analysis and discriminant analysis on training and test data sets.

The mathematical background of the program was based on well-known techniques in statistics and mathematics. To find raw canonical coefficients, the following procedures were used:

$$\mathbf{Bv} = \lambda \mathbf{Wv} \qquad (1)$$

where λ is the eigenvalue, $\mathbf{v}$ is the eigenvector corresponding to λ, and $\mathbf{B}$ and $\mathbf{W}$ are matrices of the between- and within-group sums of squares and cross products. For a more detailed description of the statistical background see Klecka, 1980 and for the mathematical background see Golub and Van Loan, 1989. The assumption was made that the matrix $\mathbf{W}$ is positive definite ($\mathbf{W}$ is always symmetric):

$$\sum_{i,j=1}^{N} y_i W_{ij} y_j > 0 \quad \text{if} \quad \sum_{i=1}^{N} y_i^2 \neq 0$$

where $\mathbf{N}$ is the number of variables. $\mathbf{W_{ij}}$ denotes the element of $\mathbf{W}$ appearing in the $\mathbf{I}th$ row and $\mathbf{j}th$ column, and $\mathbf{y_i}$ is the $\mathbf{I}th$ element of vector $\mathbf{y}$. The matrix $\mathbf{W}$ can be represented as a product of two matrices:

$$\mathbf{W} = \mathbf{LL^T} \qquad (2)$$

where $\mathbf{L}$ is a nonsingular lower triangular matrix ($\mathbf{L_{ij} = 0}$ **for** $\mathbf{j \geq I + j}$), and $\mathbf{L^T}$ is a transpose matrix obtained from $\mathbf{L}$ by interchanging rows and columns. Substitution of equation 2 into equation 1 yields:

$$\mathbf{Bv} = \lambda\, \mathrm{LL}^{\mathrm{T}}\mathrm{v}$$

Define $\mathbf{y} = \mathbf{L^T v}$, then calculate

$$\mathbf{B(L^{-1})^T y} = \lambda \mathbf{Ly}$$

or

$$\mathbf{L^{-1}B(L^{-1})^T y} = \lambda \mathbf{y}$$

Denoting $\mathbf{A} = \mathbf{L^{-1}B(L^{-1})^T}$, the symmetric standard eigenproblem:

$$\mathbf{Ay} = \lambda\mathbf{y} \qquad (3)$$

because matrices **B** and hence **A** are symmetric. The eigenvalues of equations (1) and (3) are the same, and the eigenvectors of equation (1) are obtained from that of equation (3) by the equation:

$$\mathbf{v} = \mathbf{(L^{-1})^T y}$$

In the program, the Cholesky method was used to compute factorization (eq. 2) and the Jacobi method for solving the complete eigenproblem (eq. 3). Inverse matrix $\mathbf{L^{-1}}$ was computed by solving **N** systems $\mathbf{Lx_i = b_i}$, $\mathbf{i = 1, \ldots N}$ where $\mathbf{b_i}$ is a vector consisting of zeroes and 1 at the *Ith* place. Because **L** is the lower triangular matrix, these systems can be solved efficiently by back substitution. The matrix $\mathbf{L^{-1}}$ is then obtained by putting together vectors $\mathbf{x_i}$, $\mathbf{I = 1, \ldots N}$.

Coefficients of canonical functions were calculated from corresponding eigenvectors by normalization $\mathbf{v^T Wv = 1}$.

In the PC module program named "DISCRIM", the inverse covariance matrix $\mathbf{W^{-1}}$ was computed using the decomposition of matrix **W**:

$$\mathbf{W^{-1} = (L^{-1})^T L^{-1}}$$

where $\mathbf{L^{-1}}$ was calculated in the same way as in the PC module program named "CANONIC", which calculated canonical functions.

The performance evaluation of the PC version of canonical and discriminant functions was done using the same data sets used with the SAS statistical package. A DELL PC was used for time estimation of the program performance. Canonical analysis of a data set of 2550 wheat kernels with seven feature vectors was performed to create two canonical functions. Computational time was 5 min 18 s. The canonical program computed two canonical values for each observation. Discriminant analysis with the same 2,550-observation data set and with two canonical values as model features, was done in 45 s. When discriminant analysis was done with a seven-feature model for 2,550 observations, computational time was 6 min 48 s. Computed discriminant functions were considered as training data. When a 2,171-observations data set was run as test data, computational time was 4 min 4 s. In this case, linear discriminant functions were computed. The DELL with 20 MHz speed did not have a math co-processor. Considering the characteristics of the PC used, performance time was quite reasonable for discriminant analysis of a sample of this size.

The recognition rates coincided with those from SAS output and were 93.4% for hard wheat and 94.7% for soft wheat for the samples tested. To compare computational cost and achieved correct recognition rate, different sets of features were tested. The best results were achieved when 47 features were used to create three canonical values and input them for computing quadratic discriminant functions. The resulting correct recognition rates were 95.5% for hard wheat and 96.4% for soft wheat. With 34-feature, recognition results were 94.4% for hard wheats and 95.5% for soft wheats. Recognition rates with seven features and linear discriminant functions were 93.4% for hard wheat and 94.4% for soft wheats with training data and 93.2% for hard wheat and 94.3% for soft wheat with test data.

Conclusions

Pattern recognition methodology was applied for classification of hard and soft wheat kernels. Feature vectors included wheat-kernel morphometry as measured by digital imaging and single-kernel hardness values provided by a hardness instrument. A data set of 4,721 wheat kernels were analyzed using multivariate statistical methods, computing canonical and discriminant functions. The data analysis showed a significantly higher recognition rate when wheat-kernel morphometry and hardness scores were combined. Comparisons were made using only morphometry, only hardness values and combinations of morphometry, and kernel weight.

To make results of the study transportable to elevators or milling companies, a PC version of the algorithm was developed and tested on a training data set and a test data set. Tests were done to confirm PC implementation of the algorithms developed. PC execution efficiency was acceptable, approximately 5 min for training with 2,550 observations and six variables. Individual kernels could be classified with stored discriminant functions in a less then 1 s per kernel (0.33 ms).

Many image digitizing boards designed for PCs and able to acquire images in real time of less than 0.33 s, are on the market. The single kernel hardness instrument achieved performance rate 110 kernel/min. Therefore, wheat kernel classification by imaging or combined with single kernel crushing would also be practical.

References

Golub, G. H. and C. F. Van Loan. 1989. *Matrix Computations*, 2nd Ed. Baltimore, Md.: The Johns Hopkins University Press.

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

Klecka, W. R. 1980. *Discriminant Analysis.* London, England: SAGE Publications Inc.

Martin, C. R., R. Rousser and D. L. Brabec. 1993. Development of a single-kernel wheat characterization system. *Transactions of the ASAE* 36(5):1399-1404.

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.

Newman, M., H. D. Sapirstein, E. Shwedyck and W. Bushuk. 1987. Discrimination of analysis of whole grain samples. *J. Cereal Sci.* 6:125-132.

Statistical Analysis Systems Institute Inc. 1991. Ver. 6.07 Ed. *SAS Users Guide*. Cary, N.C.: SAS.

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

Thomson, W. H. and Y. Pomeranz. 1991. Classification of wheat kernels using three-dimensional image analysis. *Cereal Chemistry* 68(4):357-361.

Zayas, I. Y., Y. Pomeranz and F. S. Lai. 1985. Discrimination between Arkan and Arthur wheats by image analysis. *Cereal Chemistry* 62(6):478-480.

Zayas, I. Y., F. S. Lai and Y. Pomeranz. 1986. Discrimination between wheat classes and varieties by image analysis. *Cereal Chemistry* 63 (1):52-56.

Zayas, I. Y and C. Martin. 1988. Image analysis and "crushing" technique for wheat class determination. *Cereal Foods World* 33(8):669. (Abstract).

Zayas, I. Y., J. L. Steele, H. Converse. 1990. Discrimination between whole and broken corn kernels by image analysis. *Transactions of ASAE* 33(5):1642-1646.

Zayas, I. Y, C. R. Martin, J. L. Steele and R. E. Dempster. 1991. Image texture analysis of crushed wheat kernels. In *SPIE Proc. on Machine Vision Architectures, Integration and Applications* 1615:203-215.