Image Analysis and Characterization of Cereal Grains with a Laser Range Finder and Camera Contour Extractor

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ABSTRACT

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An image analysis system with the capability to acquire and combine three-dimensional laser range data and two-dimensional camera contour extracted images was used to discriminate between cereal grains and weed seeds and between soft white and club wheats, two- and six-rowed barleys, and rye and triticale kernels. Discriminant functions were established to discriminate between wheat and nonwheat with 99.5% accuracy and between nonwheat and wheat with 98.3% accuracy. The discrimination between two soft white and two club wheats was about 90% accurate. The discrimination between two- and six-rowed barley was about 90% accurate, between barley and other grains 97% accurate, and between rye, triticale, and other grains 90% accurate. Discrimination between wheat, soybeans, oats, wild oats, dent corn, flint corn, wild buckwheat, sorghum, and lamb's-quarter was almost 100% accurate.

Rapid advances in microcomputer technology have made it possible to apply techniques from image processing and pattern recognition to automated, objective visual systems. Several recent studies reported on the use of computerized image analysis in characterization of cereal grains (Zayas et al 1985, 1986a,b; Sapirstein et al 1987; Neuman et al 1987). Some of those studies employed gray level two-dimensional (2-D) images from a video camera for feature extraction. Subsequent discrimination and identification were based on those features. The capability of such visual systems may be limited because of insufficient information contained in the 2-D images. The most obvious limitation of 2-D images is the lack of information about height (or depth) dimensions and relations, which play an important role in visual inspection. Thus, for instance, certain crease depth and germ height dimensions in wheat classes and varieties and their relationships are important in wheat characterization, processing, and end-use properties (Pomeranz 1982).

The objectives of this study were to develop a low-cost, integrated image analysis system with three-dimensional (3-D) profile and 2-D image contour acquisition capabilities. The system was evaluated in discrimination between wheat varieties (soft white and club), between wheat and nonwheat cereal grains (corn, barley, rye, oats, triticale, and sorghum), and between cereal grains and soybeans or weeds (wild oats, lamb's-quarter, and wild buckwheat). For terminology used in this report and for general information on image analysis, see Rosenfeld and Kak (1982), Duda and Hart (1973), and Gonzalez and Wintz (1987). Information on lasers and their application can be found in Luxon and Parker (1985).

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MATERIALS AND METHODS

Position Sensor-Based Laser Range Finder

Optical scanning mechanism. Range finders (3-D data) are noncontact sensors that provide a set of three-dimensional surface points of object and background. Range data calculations are based on either the time-of-flight or the triangulation principle (Parthasarathy et al 1982). For the time-of-flight technique, the range data are obtained by measuring the phase difference between transmitted and received beams. This technique either requires a laser with power greater than 15 MW, a potential safety hazard, or acquires range data at a very low rate. Also, the required time resolution is difficult to obtain for higher resolution of depth. Thus, to resolve height differences of 0.001-in., a time delay resolution of better than 0.1 picoseconds is necessary (Jarvis 1983). Therefore, we utilized in this study the triangulation principle in producing 3-D data. A position-sensitive sensor was used to calculate relative height profile. This arrangement eliminated time-consuming triangular computation of absolute height.

Figure 1 depicts the set-up of our laser scanning mechanism. A low-power (10 MW) helium-neon laser beam projects a spot of light on an object surface. A portion of the light is scattered from the surface and is converged by the imaging lens onto a position sensor. When the laser beam hits a higher surface, there is a small corresponding displacement of the image on the sensor along the direction normal to the scanning line. The small displacement is proportional to the change in height of the object at that point and can be approximated by $H = KD$, where K is a constant depending on the angle between the surface of sensor and the laser line and the distances of object and sensor from the imaging lens. With the rotating polygon mirror, which has 24 equally sized mirrors on its perimeter, a scanning line is formed by the continuously changing angle of the individual mirror. Calculating the displacement, D, on a position sensor along the direction perpendicular to the scanning line results in a relative height profile without calculating the absolute H. To obtain absolute data, a calibration can be done by displaying an object with known H and determining the proportional factor K between H and D. By placing the object on a movable table and moving the object incrementally in the direction perpendicular to the scanning line, the volume of the 3-D object image can be acquired by summing the integrated scanning height profiles.

Position sensor and height profile. The vertical displacement, D, which is proportional to the height of the object, can be measured easily by the electrical currents from the position sensor as demonstrated in Figure 2.

The horizontal scanning line was imaged onto the position sensor as a sequence of light spots. Each light spot generates a pair of photo currents (I_a, I_b) proportional to its displacement from the horizontal center line. The relative vertical position of the light spot X, with respect to the horizontal center line of the sensor, can be calculated from the equation $X = I_a - I_b / I_a + I_b$. Thus, if X falls on the center of the sensor, where $I_a = I_b$ then X has a relative position value of 0.

Electronic Interfacing: Design and Implementation

An IBM PC XT was used as the host computer for acquiring, storing, and processing the scanned data. Interfacing between the laser scanner and PC is depicted in Figure 3. The laser scanner sends information about the object's surface to the position sensor board in terms of sequence of reflected laser light spots. The position sensor board converts the optical data, which is represented by currents I_a and I_b, into voltage signals and feeds them to the A/D (analog-to-digital converter) and FIFO (first in first out memory storage) board. The A/D and FIFO board converts the analog voltage signals to binary digital signals and buffers them to the host PC for height profile computation. Timing control signals for the position sensor board and the A/D and FIFO board are generated by the timing board. Inputs for the timing board are provided by a 110 (input-output) address board, in which the control command generated from the host PC is converted into proper data format for the timing board. Details of the position sensor board, A/D and FIFO board, timing board, and 110 address board as well as program source listing for the host PC are available from author Y. P. Chiang.

The A/D and FIFO board include two 8-bit A/D flash converters, which encode the input voltages into binary formats ranging from 0 to 255, and two 1,024-byte FIFO memories, which are used as buffer storage for 1,024 pairs of scanned data. This memory is also accessible to the host PC.

The rise time for the position sensor is about 2,000 nsec. The clock rate on the timing board is generated by a 4-MHz oscillator. The 110 address and the timing board generate all the basic control signals. The actual host PC 110 addresses for these boards are configured via a mapping switch on the 110 address board.

For scan line acquisition, a special software program, LINE-SCANNING, was developed using TURBO Pascal on the host PC. This program allows the host PC to read in pairs of 1,024 sampling data from the A/D and FIFO board and calculates the corresponding height profile. Image smoothing was then applied to produce a graph of line position versus height profile. This graph is drawn on the PC monitor in color or can be saved on hard disk for future processing.

Prototype specification. The position sensor board uses an SC-10D device from United Detector Technology, Hawthorne, CA, as the position-sensing detector. The position sensor records the image at the focus point of the imaging lens (1× magnification).

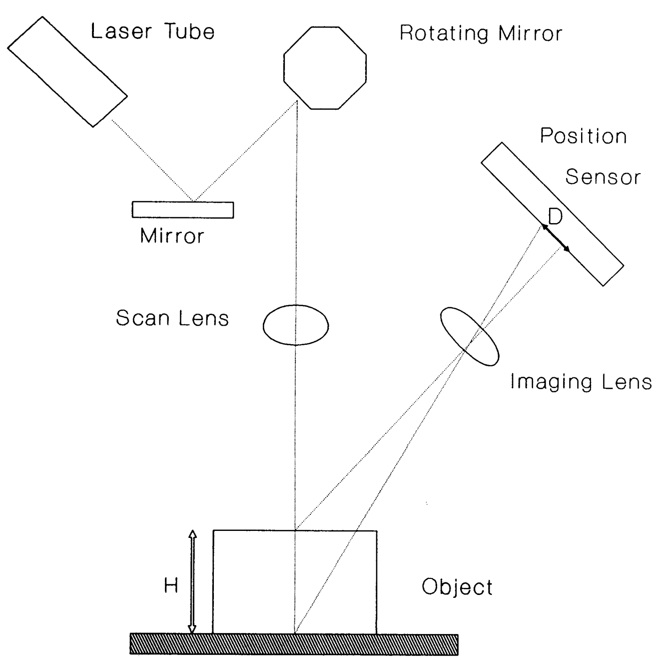

Fig. 1. Laser scanning mechanism.

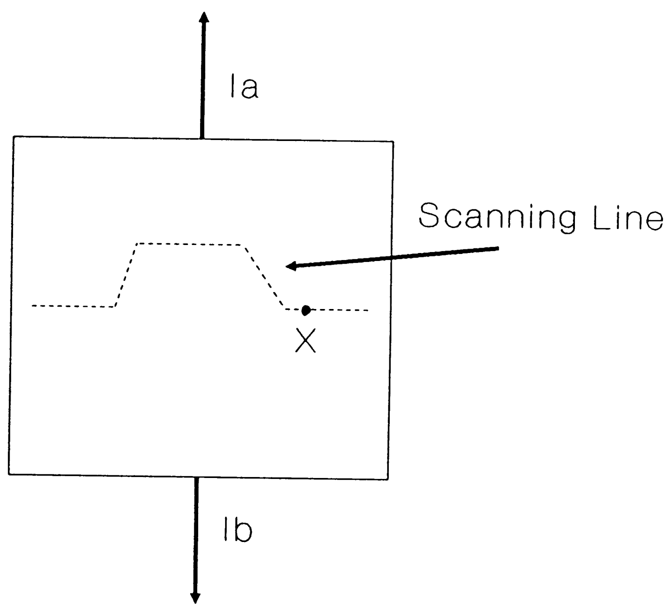

Fig. 2. Height profile on position sensor.

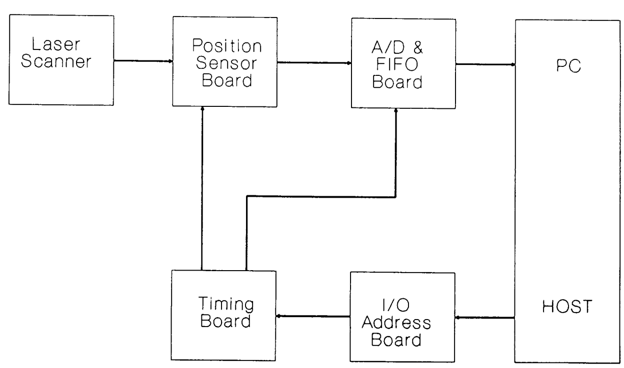

Fig. 3. Block diagram of laser ranging system.

Thus, the image has the same size as the object when it is recorded by the sensor. This means that the maximum size of an object to be scanned is limited by the physical size of the sensor, which is 1.3 cm $\times$ 1.3 cm. The sensor's spatial resolution is about 1.3 cm/256 pixels or 0.05 mm/pixel, the accuracy of which is affected by random photon scattering and is about ± 4 pixels (i.e., 0.2 mm).

Increasing the maximum measurable size of the object is possible by changing the angle and distance of the position sensor with respect to the object (Fig. 1). However, this is done at the expense of reduced spatial resolution.

The interfacing electronic circuitry was designed and implemented on a PC extension board and is inserted into a host IBM PC XT with a 4-MHz system clock.

Camera Contour Extractor

To compensate for the range finder's limitation and to enhance its flexibility in dealing with different imaging applications, a commercial image acquisition board was integrated into the host PC to serve as part of a 2-D image contour extractor.

The complete extractor hardware includes a Sony XC-39 CCD (charge coupled device) video camera module with a Tokina macro TV lens (25 mm, F 1.4), the image acquisition board, PC Vision (Imaging Technology, Inc., Woburn, MA), and a high-resolution display monitor. The block diagram shown in Figure 4 illustrates the whole system. The system scans the height profile and extracts contour of the object via laser ranger board and PC Vision board, respectively. Both height profile and contour images are then stored in the host PC for future processing.

Contour extraction. One image frame taken through the CCD camera is stored/represented in the frame memory by 512 $\times$ 512 8-bit array (256K pixels with 256 grey levels for each pixel). The frame memory on the PC Vision board is divided into four 64K-byte blocks. That is, a complete 512 $\times$ 512 image frame takes four blocks. At any time, only one block is mapped onto the

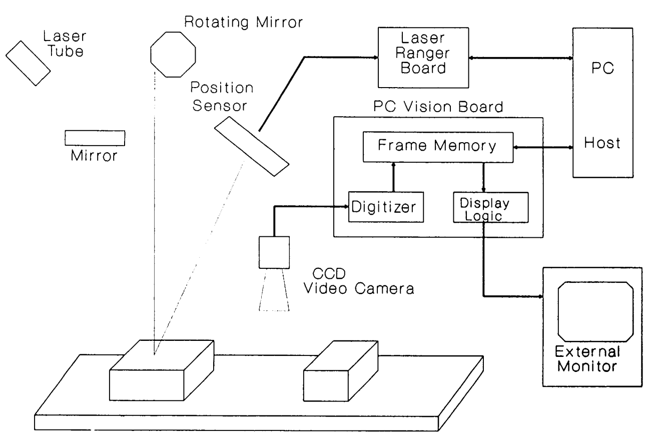

Fig. 4. Integrated range-finding and contour-extracting system.

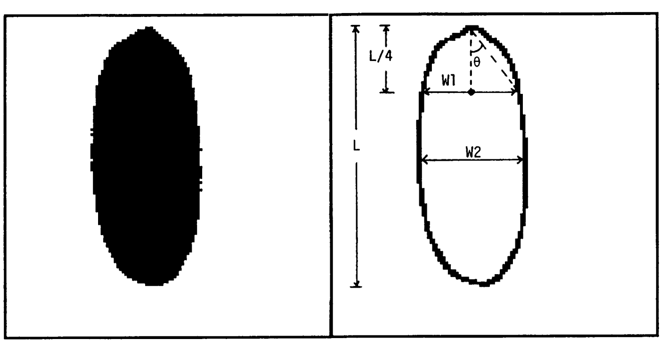

Fig. 5. Left, wheat image silhouette printed by Hewlett Packard Laserjet. **Right,** extracted wheat contour. L = maximum length, W_1 = width at L/4 from brush end, and θ = angle describing sharpness of brush end; ● = center reference.

64K-byte addresses in the PC memory space. We used a uniformly dark background and two ordinary 75 W lamps for lighting the object from two sides. Individual grain images are acquired with a spatial resolution of 0.02-mm pixel when viewed from a distance of about 1.75 cm with the 25-mm macro lens. Through gray level histogram analysis of the acquired image, a threshold value was chosen. Every pixel with an array level greater than or equal to the threshold will be changed to black and those with less than the threshold will be changed to white. This results in a well-contrasted silhouette. Then, using the Sobel edge operator, which captures pixels differing from their neighbors, the grain's contour was produced. Figure 5 gives a typical extracted wheat silhouette and the corresponding contour.

A program called Grain-Edge was developed in the host PC using TURBO Pascal to perform the grain-contour-extracting tasks as described above. Complete source listing is available from Y. P. Chiang.

Feature Parameter Selection and Image Analysis

Based on the images acquired by the laser range finder and the CCD camera contour extractor, a set of kernel feature parameters with the potential to be used in discrimination among various grains was selected. The kernel features and their acquisition methods were as follows:

With kernel crease up, the scanning line was applied perpendicular to the length of the kernel and at about one-fourth of the total length measured from the brush end. A typical height profile of the wheat kernel and the definitions of the related feature parameters, CW, CH, OS, CS, are shown in Figure 6.

With kernel crease down, the scanning line was applied parallel to the length of the kernel. The graph of this profile and the extracted feature parameters, GL, GD, H, GS, BS, are defined in Figure 7.

Two additional feature parameters, MD and AD, were obtained from the above mentioned height profile. MD is the maximum value of the first derivative of each point X along the height profile. AD is the average of all those derivatives. That is, a larger MD indicates an abrupt change of the kernel surface, and a larger AD indicates many abrupt changes of the surface. Those two parameters were selected to represent the smoothness on the surface of the kernel along the scanning line.

From the extracted contour, Figure 5b, an additional set of feature parameters was defined as follows:

L, maximum length.

W1, width at L/4 from the brush end.

W2, the largest width within the length of the kernel.

AR, area bounded by the contour. This is computed through

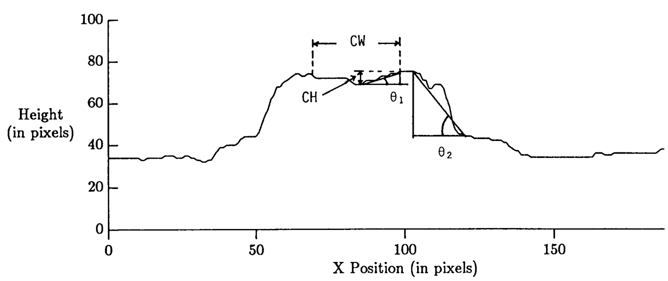

Fig. 6. Typical wheat height profile with crease up.

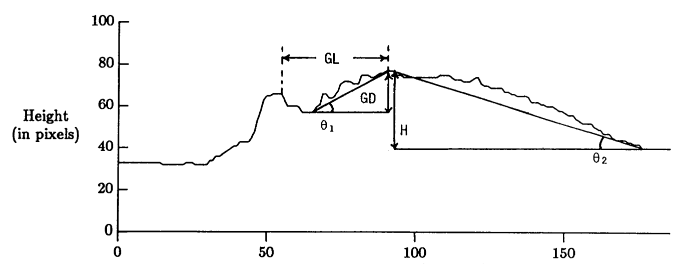

Fig. 7. Typical wheat height profile with crease down.

the integration of the pixel numbers within the contour.

HS, the sharpness of the brush end, which is defined by tan (θ), where θ is defined as in Figure 5b.

RM and RV. The upper fourth of the kernel, brush end, is treated as a curve with reference center at (W1/2, L/4). This curve is referred to as brush end in this paper. Let radius (i) represent the distance between the ith edge pixel on the brush end and the reference center. The relative degree of the brush end roundness can be represented by the standard deviation among all its radii. The parameters RM and RV stand for the average radius and the standard deviation among all radii. The formula for RM is

$$RM = \Sigma \text{ radius } (i)/n \text{ for } i=1, 2, \ldots, n$$

and

$$RV = \sqrt{\Sigma[\text{radius } (i) - RM]^2/n}$$

where n is the number of edge pixels on the brush end. The rounder the brush end, the lower the RV.

Stepwise discriminant analysis was performed to determine the relative importance in the discrimination of the feature parameters from the range and contour images (SAS 1985). This analysis was applied to three pairs of samples: between the soft white wheat (SW) Lewjain and the club wheat Tres, between the club wheat Tres and soybeans, and between dent corn and flint corn. Stepwise discriminant analysis allows us to select a subset of kernel features that has dominant discrimination capability. The reasons for selecting these three pairs—Lewjain and Tres, Tres and soybeans, and dent corn and flint corn—were their differences in range, contour, or both. Daws (SW) and Tyee (club) as well as Lewjain (SW) and Tres (club) wheats are quite similar in their image shape. No single feature can satisfactorily discriminate between them. Tres and soybeans have large differences in range data. Dent corn and flint corn are similar in range features, and can be discriminated by their 2-D contour feature parameters.

The feature parameters selected by the stepwise discriminant analysis constituted a primary set of kernel features. This primary set of kernel features, including both range and 2-D contour features, was used as the set of quantitative variables for analysis in the final evaluation of the discrimination results. Discriminant analysis also generated a function that can be routinely used for further grain discrimination.

The discrimination process consisted of the following three steps: 1) from range and 2-D image data the feature parameters likely to be useful as discriminants were defined; 2) stepwise discriminant analysis was used to determine an optimal subset of feature parameters; and 3) discriminant analysis was used to evaluate the discrimination result and develop a discriminant function.

Both the stepwise discriminant analysis and the discriminant analysis were done using SAS on an IBM 3090 main frame computer. This was done to utilize the larger instrument's fast complex statistical computation capability. The resulting discriminant function was then adopted as a basic discrimination criterion.

Grain Samples

Wheat samples were obtained from the Western Wheat Quality Laboratory, ARS-USDA, Pullman, WA. They included the SW varieties Daws and Lewjain, and the club varieties Tyee and Tres. Dent and flint corn, two-rowed, six-rowed, and naked barley; rye, oats, sorghum, triticale, and soybeans, as well as wild oats, wild buckwheat, and lamb's-quarter were from the Seed Laboratory, Washington State University, Pullman, WA.

The wheat, various cereal grains, soybeans, and grain weeds are shown in Figure 8. Only whole nonshriveled kernels were used for analysis.

Analysis

The sample kernels were positioned manually under the fixed laser scanning line and the camera for extracting range and contour images. The programs called kernel-feature-extracting and grain-feature-computing were developed using TURBO Pascal on the host PC for range and contour feature extraction, respectively. They are available from author Y. P. Chiang.

The extraction process was evaluated by running the program on 10 subsamples of 50 kernels each. Based on all subsamples for a single grain, the coefficients of variation (%) for the major feature parameters were: L, 0.6; W1, 0.1; W2, 0.1; AR, 1.2; RM 0.4; RV, 0.2; H, 0.6; AD, 1.2; MD, 1.1; GL, 2.9; BS, 1.1; GS, 2.7; CS, 2.6; OS, 3.1; CH, 2.7; CW, 2.8; GD, 3.1.

TABLE I
Summary Ranking of Kernel Features

Grains/ Variable	Number of Kernel Features	Partial R^2	ASCC[a]
Tres and Lewjain wheats			
Entered			
L	1	0.4171	0.4171
W2	2	0.2581	0.5675
RM	3	0.2386	0.6707
Removed			
L	2	0.0004	0.6706
Entered			
H	3	0.0503	0.6871
AD	4	0.0415	0.7001
Tres wheat and soybeans			
AD	1	0.9116	0.9116
H	2	0.6889	0.9725
Dent corn and flint corn			
L	1	0.9996	0.9996
AR	2	0.9540	0.9998
RV	3	0.5394	0.9999

[a] Average squared canonical coefficient.

TABLE II
Discrimination Criteria for Club Wheat Tres and Soft White Wheat Lewjain

Parameter	Tres	Lewjain
Constant	−4,667.80	−4,748.84
L	39.13	39.69
W2	77.32	77.00
AR	−0.67	−0.68
RM	105.88	108.29
RV	37.41	40.42
H	0.56	0.46
AD	−44.03	−41.93

Fig. 8. Representative kernels used in this study. Top row (from left to right): dent corn, flint corn, lamb's-quarter, wild buckwheat, sorghum. Center row: soybean, rye, triticale, naked barley, two-rowed barley, six-rowed barley. Bottom row: wild oats, oats, soft white wheat Daws, club wheat Tyee, soft white wheat Lewjain, and club wheat Tres.

TABLE III
Discrimination Summary of 10 Grain Types[a](%)

	Tres	Tyee	Lewjain	Daws	Barley-2	Barley-6	Barley-N	Triticale	Rye	Oat
Tres	84	2	0	12	0	0	2	0	0	0
Tyee	0	90	2	8	0	0	0	0	0	0
Lewjain	2	2	70	26	0	0	0	0	0	0
Daws	8	2	20	70	0	0	0	0	0	0
Barley-2	0	0	0	0	84	10	2	2	2	0
Barley-6	0	0	0	0	28	70	2	0	0	0
Barley-N	6	0	0	0	0	0	94	0	0	0
Triticale	0	0	2	4	0	0	8	84	0	2
Rye	0	16	0	0	0	0	0	16	68	0

[a]The seven grain types not shown had a 100% accurate discrimination. The summary table was based on test set data. Training set data showed the same or better results.

RESULTS AND DISCUSSION

Feature Selection via Stepwise Analysis

The SAS discriminant analysis package was used to classify Tres versus Lewjain, Tyee versus Daws, Tres versus soybean, oats versus wild oats, two-rowed versus six-rowed barley, naked barley versus triticale versus rye, dent corn versus flint corn, buckwheat versus sorghum versus lamb's-quarter, and finally all grain types versus each other. Two sets of data were used for each grain type: training sets and test sets. The training sets were used for feature selection.

A set of seven feature parameters was selected on the basis of the analysis summary from three pairs of samples, as shown in Table I. As mentioned earlier, these three pairs of samples require 2-D contour and/or range features in order to achieve a satisfactory discrimination. Thus, this set of features is adequate for discrimination among the various grains (wheat, corn, barley, rye, oats, sorghum, triticale, and soybeans) and grain weeds (lamb's-quarter, wild oats, and wild buckwheat) which have discriminative features in either 2-D or range images, or in both. The selected feature parameters are: average first derivative of height profile (AD from the laser scanning image) with crease down, height (H from the laser scanning image) with crease down, area (AR from the extracted contour image), maximum length (L from the extracted contour image), maximum width (W2 from the extracted contour image), the mean brush end roundness (RM from the extracted contour image), and the variance of brush end roundness (RV from the extracted contour image).

Range features AD and H were dominant parameters for the discrimination between Tres wheat and soybeans. On the other hand, for discrimination between dent corn and flint corn, 2-D contour features were satisfactory. For the most difficult discrimination between Tres and Lewjain wheats, parameters from both range and contour features were required.

From Table I the value of partial correlation coefficients (R^2) provides a ranking among features according to the individual ability to discriminate between the specific classes. The average squared canonical coefficient (ASCC) indicates explained percentage of the variability between classes by taking every feature as a canonical variable. Based on these values a canonical discriminant function was calculated by SAS as reported in Table II (only data for the pair of Tres and Lewjain are shown). Using the established discriminant function from Table II for a blend of Tres and Lewjain, it was possible to identify correctly 92% of Tres kernels (8% missed) or 96% of Lewjain kernels (4% missed).

As mentioned earlier, two sets of data were used for each grain type. The training sets were used for selecting feature parameters. Then the chosen seven parameters were used for the test sample discrimination among groups of grain as well as among all grain types. This paper only reports the discrimination results among all grain types. To simplify the presentation, only less than perfect (100%) discriminations are listed. Those results are summarized in Table III. When all seven variables in Table II were used for the discrimination of the 17 types of grain in this study, seven types were discriminated correctly every time; those are not included in Table III. In 10 grain types, some of the kernels were not discriminated correctly. Those types are listed in Table III. Only results of test data are included; they were equal to or poorer than the calibration data. The main incorrect discriminations were between club and soft white wheats, two- and six-rowed barleys, and triticale and rye. Those are, of course, the most difficult to discriminate. Still, even in those cases the combined 2-D and 3-D image analysis system provided very promising discrimination that could be adapted for rapid, reliable, and objective characterization and distinction between wheat and nonwheat and among various types of cereal grains. Such work is underway in our laboratories.

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