Frequency Domain Image Analysis for Detecting Stress Cracks in Corn Kernels

Y. J. Han
Clemson University

Y. Feng
Clemson University

Curtis L. Weller
University of Nebraska-Lincoln, cweller1@unl.edu

FREQUENCY DOMAIN IMAGE ANALYSIS FOR DETECTING STRESS CRACKS IN CORN KERNELS

Y. J. Han, Y. Feng, C. L. Weller

ABSTRACT. *A corn kernel classification procedure was developed in the frequency domain using a two-dimensional Fourier Transform for inspection of stress cracks. Investigations were also conducted to define suitable conditions and optimum image resolution for viewing stress cracks in corn kernels using a computer vision system. A pre-processing procedure included contrast enhancement, edge enhancement, and kernel edge elimination to improve stress crack recognition. A Fast Fourier Transform algorithm was applied to the pre-processed images, and the transformation results were condensed into 33 feature signatures representing position or orientation invariant morphological features. A multi-variate discriminant analysis and multiple regression analysis were used to develop classification criteria for stress crack inspection. Both methods were able to detect stress cracks satisfactorily with an average success ratio above 96%.*
Keywords. *Machine vision, Image analysis, Fourier transform, Corn and rice quality.*

Corn is one of the most important agricultural products in the United States. It has emerged and remains a major feed crop for both domestic use and export. More recently, corn has become an important raw material for producing industrial products, such as ethanol (Feng, 1992).

External and internal damage may exist in the kernels of corn. External damage includes cuts and abrasions in the pericarp. Internal damage appears in the form of stress cracks in the endosperm (Thompson and Foster, 1963). Cracked and broken kernels within batches of corn make aeration difficult and invite attack by fungi and insects, reducing market value and shortening storage life.

At present, evaluation of corn kernels for various defects is done by visual inspection or breakage susceptibility tests. Stress cracks are still being evaluated by a candling procedure. Such methods are time-consuming and are often inconsistent due to fatigue of the human eyes. An automatic method for defect detection would provide rapid and consistent results. This would enable evaluation of large samples of corn to accurately determine corn quality.

Stress cracks are internal fissures that can be observed in kernels by a candling technique or by x-ray inspection. Gunasekaran et al. (1985) investigated the size characteristics of stress cracks of corn kernels from four varieties using scanning electron microscopy. Stress cracks were observed to originate at the inner core of the floury endosperm and propagate radially outward along the boundary of starch granules. Many cracks did not advance as far as the pericarp layer. They concluded that a typical stress crack is about 53 μm in width and half the kernel in depth.

Laser optical methods were successfully applied to detect external kernel damage using reflectance difference (Gunasekaran et al., 1986). Gunasekaran concluded that difference in light reflectance was not sufficient to detect stress cracks because light reflectance is a surface phenomenon. Ultrasonic imaging was found unsuitable because the kernel needed to be thinly sliced to obtain a visual image (Gunasekaran and Paulsen, 1986). Based on their investigation of several nondestructive testing techniques, they reported that an optical image processing method is most suitable for automatic stress crack detection.

Image processing was used to inspect stress cracks of corn kernels by Gunasekaran et al. (1987). The back lighting mode with a black-coated plate as a background was adopted to obtain images with high contrast between the stress cracks and the rest of the kernel. They developed image processing algorithms to extract the stress cracks as streaks or lines. The proposed algorithm was able to detect stress cracks in 90% of the kernels examined. They also observed that the single and multiple stress-cracked kernels required careful positioning over the lighting aperture in order to obtain complete details of the stress cracks.

Han and Feng (1994) studied the feasibility of frequency domain inspection using a two-dimensional Fast Fourier Transform (FFT). The FFT was condensed to 33 feature signatures, which consisted of 16 ring features, 16 wedge features, and a DC component. The DC component and each of the 16 ring signatures represented orientation invariant features with specific bandwidths of spatial frequencies, starting from DC component at the center of

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The authors are **Young J. Han,** ***ASAE Member Engineer,*** Associate Professor, and **Yi Feng,** former Graduate Assistant, Dept. of Agricultural and Biological Engineering, Clemson University, Clemson, South Carolina; and **Curtis L. Weller,** ***ASAE Member Engineer,*** Associate Professor, Dept. of Biological Systems Engineering, University of Nebraska, Lincoln. **Corresponding author:** Young J. Han, Clemson University, Dept. of Agricultural and Biological Engineering, 229 McAdams Hall, Clemson, SC 29634-0357; telephone: 864-656-4046; fax: 864-656-0338; e-mail: <yhan@clemson.edu>.

the image and higher frequency components moving out radially. The 16 wedge signatures represented orientation-specific features. These 33 signatures were analyzed by multivariate discriminant analysis. This procedure was applied to egg shell inspection, and demonstrated an 88% success ratio in identifying egg shell cracks.

OBJECTIVES

The objectives of this study were to develop an image analysis procedure for the inspection of corn kernel stress cracks using a frequency domain inspection technique, and to evaluate the effect of different corn varieties and image resolution on the system performance.

EQUIPMENT AND PROCEDURES

PREPARATION OF CORN KERNEL SAMPLES

Approximately 9.1 kg (20 lb) for each of two hybrids of dent corn, Pioneer 3165 and Pioneer 3147, were harvested by hand from a field in the Calhoun Experimental Fields at Clemson University. The corn samples, at approximately 35% w.b. (wet basis) moisture content, were dried at ambient room conditions to approximately 9.1% moisture content w.b. before being stored in sealed plastic bags at 2°C.

To develop stress cracks in corn kernels of Pioneer 3165, dry kernels were first soaked in distilled water for 30 min. The water was drained and the kernels were dried using a convection oven at 105°C for 30 min. After drying, the kernels were left to cool at room temperature, approximately 18°C. The same procedure was applied to the corn kernels of Pioneer 3147, except the soaking time was 150 min and the drying time was 60 min. Different times were used to get adequate stress cracks in each kind of corn kernel.

There were 1,000 kernels of Pioneer 3165 and 600 kernels of Pioneer 3147 used in this study. In the Pioneer 3165 samples, 500 kernels contained stress cracks, and 500 were without stress cracks. In the Pioneer 3147 samples, 300 were stress-cracked, and 300 were without stress cracks.

MACHINE VISION EQUIPMENT

The image processing hardware used in this study consisted of a frame grabber board (PCVISION*plus*, Imaging Technology Inc., Woburn, Mass.) running on a 16 MHz 80386 microcomputer. The frame grabber had a 512 × 480 spatial resolution with 256 gray-levels. Images were captured by a CCD camera (Panasonic® model WV-CD50) with 12.5-75 mm Fl.2 zoom lens and displayed on an RGB analog monitor (Sony® Model PVM-1271Q).

A commercial software library, Prime Factor FFT™ from Alligator Technologies (Costa Mesa, Calif.), was used to implement a two-dimensional FFT. Unlike many other FFT routines, the prime factor FFT algorithm did not require two-dimensional arrays be square, and that each dimension need not be a power of 2. A detailed explanation about the prime factor FFT algorithm can be found in Nussbaumer (1982).

IMAGE ACQUISITION

Investigations were conducted to define a suitable condition for viewing stress cracks in corn kernels using a computer vision system. In this study, kernels were illuminated using front lighting and back lighting. Front lighting was achieved by a pair of quartz-halogen lamps mounted on either side above the kernel at a 45° angle. Illumination was directed toward the single kernel in the center of the field of view of the camera. Back lighting consisted of a one quartz-halogen lamp directly below a black plate with a small aperture. A kernel was placed over the aperture drilled in the background. Three different aperture sizes of 0.3, 0.5, 0.7 mm were used for comparison. The light source illuminated the sample through the aperture, and the light was transmitted through the sample kernel to a camera located directly above the sample.

Images produced by front lighting had lower contrast than those with back lighting. The front lighting could only bring out the very serious stress cracks, but was not sufficient enough to bring out the relatively faint stress cracks in corn kernels. Changing background colors and use of optical filters did not enhance the details of faint cracks by using front lighting. Based on the results, the rest of the experiment was performed with the back lighting.

For back lighting, the effects of the three different aperture sizes (0.3, 0.5, and 0.7 mm in diameter) were compared for the detection of stress cracks in kernel images. The smallest opening, 0.3 mm in diameter, failed to provide high enough contrast over the whole corn kernel. Insufficient contrast was achieved when cracks were widely distributed rather than concentrated around the kernel's center. The 0.5 mm opening was better in bringing out stress cracks along the side of a corn kernel. The 0.7 mm opening did not eliminate light dispersion through edges of the kernel very well. The dispersed light was much brighter than the light transmitted through the kernel and became the dominant feature. The opening of 0.5 mm was selected to allow detection of cracks over a whole corn kernel and to reduce light scattering through the sides.

IMAGE PRE-PROCESSING

In order to obtain better stress crack recognition, a contrast-enhancement operation was performed followed by edge enhancement. First, a threshold operation removed the background by setting pixel values below a chosen value (GL) to zero. Next, the maximum gray-level value in the image was found (GH), and a histogram equalization operation (Gonzalez and Wintz, 1987) was performed to change the gray-level range from 0 to 255. The lower limit GL was chosen to be 20 by examining the histogram of the original images of corn samples. After contrast enhancement, a Roberts filter (Gonzalez and Wintz, 1987) was applied for edge enhancement.

Since any edge enhancement algorithm enhances not only stress cracks but also the edges of corn kernels, edge elimination was necessary to remove unwanted edges of kernels. The coordinates of points on the outside edges of corn kernels were found by scanning each column from top to bottom. As background gray-level values were set to zero, the top edge of the corn kernel was found as the first point with a nonzero gray-level values. The bottom edge was found in the same manner by scanning from bottom to top. These edge positions were stored in a data structure for each column in which edges were found. For each point, P(x,y), found on the outside edge, gray-level values of any point within four pixels of P(x,y) were set to zero to eliminate edges.

The FFT was applied to each pre-processed image, and each transformed image was integrated into 16 ring signatures, 16 wedge signatures, and a DC value as described in Han and Feng (1994).

Discriminant Analysis

Two discriminant analysis techniques were used to classify individual observations into one of two groups, corn kernels with and without stress cracks.

The first approach was to utilize multivariate discriminant analysis procedures contained in SAS (*SAS User's Guide*, 1985). The STEPDISC procedure was used to select a subset of significant variables for kernel classification from a calibration set of 200 corn kernels. A significance level of 0.15 was used as a criterion for adding or deleting variables from the model. The selected variables were used in the DISCRIM procedure to compute a discriminant model. The model was determined by a measure of generalized squared distance (Mahalanobis distance), based on within-group covariance matrices. The classification criterion was then applied to the test set of corn kernels during the same execution of the DISCRIM procedure.

Since the model selected by STEPDISC was not necessarily the best model (*SAS User's Guide*, 1985), and the generalized squared distance was too computationally intensive to be included in an on-line inspection algorithm, a second method used multiple regression analysis for comparison. The SAS procedure RSQUARE was used to examine a large number of models with varying numbers of independent variables. Several models with large R^2 values were selected to generate multiple regression equations using the REG procedure. A numerical quantity of 0 was assigned as the class of corn kernels without stress cracks, and 1 was assigned as the stress-cracked kernels. Output values from the regression equations were thresholded to define discriminant functions. The threshold value for each model was set where the probability of committing a Type I error (good corn kernels classified as stress-cracked kernels) would be the same as that of a Type II error (stress-cracked corn kernels classified as good kernels). These regression models and their threshold values were calculated off-line and programmed into an online inspection algorithm to classify the test set of corn kernels.

Inspection Evaluation

The above procedures were applied to Pioneer 3165 samples. These samples included a wide variety of defects, ranging from kernels with a single stress crack to multiple stress cracks to corn kernels which were shattered. The sample kernels were grouped into two category, with and without cracks, by visual inspection by a person who were familiar with stress cracks.

Among 1,000 Pioneer 3165 samples, 100 corn kernels with stress cracks and another 100 kernels without stress cracks were randomly selected from each quality class to form a calibration set. The remaining 400 good and 400 stress-cracked corn kernels were used as a test set. The discriminant functions were derived and classification criteria were determined from the calibration set. These classification criteria were used for the inspection of the test set to obtain the correct classification ratio for each discriminant function.

In order to compare the effect of a different hybrid of corn kernels, the same image processing and analysis procedures were applied to corn kernels of Pioneer 3147. For this purpose, 600 images were acquired and processed. Among these 600 corn kernels, 300 were good, 300 were with stress cracks. The calibration set was formed by randomly selecting 100 good corn kernels and 100 stress-cracked corn kernels. The test set consisted of the remaining 200 corn kernels from each quality class.

The effect of different image resolutions was studied by reducing the image resolution and applying the same inspection procedure. Images of 300 corn kernels were acquired with window sizes of 100 × 100 pixels, 84 × 84 pixels, 70 × 70 pixels, 50 × 50 pixels, and 30 × 30 pixels. The same pre-processing and statistical analysis described above were applied to these images.

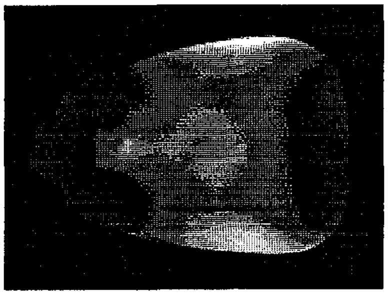
Results and Discussion

Images of good and stress-cracked kernels are shown in figures 1 and 2 with their respective Fourier Spectrum. In these two figures, the upper-left quadrant shows the original image of a kernel, the lower-left quadrant shows the image of the kernel after pre-processing, and the upper-right shows its Fourier spectrum. Since the Fourier spectra for most images decrease rather rapidly as a function of increasing frequency; and therefore, their high frequency terms have a tendency to become obscured when displayed in image form, the following transform (Gonzalez and Wintz, 1987) was used to display the Fourier spectra in figures 1 and 2:

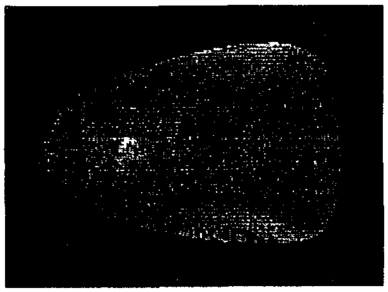
$$D(u,v) = \log(1 + |F(u,v)|) \qquad (1)$$

where $|F(u,v)|$ is the magnitude of the Fourier spectrum, and D(u,v) is the function displayed in figures 1 and 2. This transform is for display only, and the integration of ring and wedge features was performed on the original values of $|F(u,v)|$ (Feng, 1992).

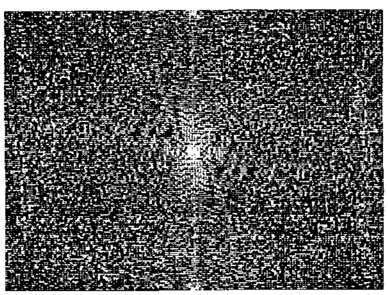
Figures 3 and 4 show the range of values of 16 ring and 16 wedge signatures calculated from the calibration set of 100 good corn kernels and 100 stress-cracked corn kernels for Pioneer 3165. Results for Pioneer 3147 showed a similar distribution. The ring and wedge values for stress-cracked kernels showed a much larger variation than those of good kernels, primarily due to the different severity of stress cracks. The variations in good kernels were caused by different shapes and sizes of corn kernels. If any one feature showed clear separation between good and stress-cracked kernels, that variable could have been used as a sole discriminant function. Since all 33 feature signatures, including the DC value, were overlapped, statistical



Original Image



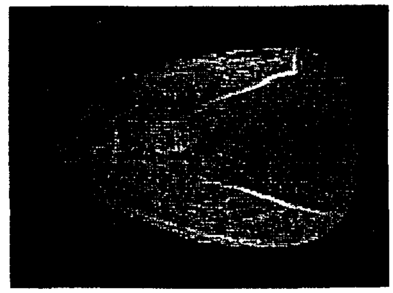
After Pre-processing



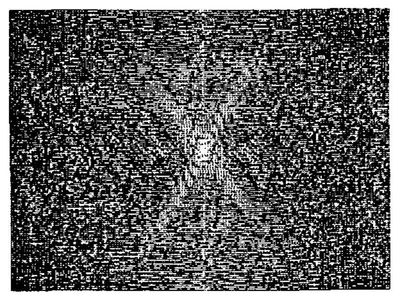
Fourier Spectrum

Figure 1–Images of a good corn kernel with its Fourier spectrum.

Original Image



After Pre-processing



Fourier Spectrum

Figure 2–Images of a stress-cracked corn kernel with its Fourier spectrum.

analysis was necessary. Considering that the DC value and the ring signatures represent specific bandwidths of spatial frequencies and the wedge signatures reflect specific directions of cracks, only the 16 ring signatures and the DC value were included in the statistical analysis as suggested by Han and Feng (1994). Since these 17 features are orientation invariant, corn kernels do not have to be positioned in absolutely consistent orientation when acquiring kernel images.

For the Pioneer 3165 calibration set, STEPDISC suggested a seven-variable subset shown in table 1. These selected variables were used in the DISCRIM procedure to compute a generalized squared distance criterion and to inspect the test set of 800 corn kernels. The classification result is shown in table 2. The correct classification ratios were 95.0% for good kernels and 97.8% for stress-cracked kernels with an average success ratio of 96.4%.

Several regression models selected by the RSQUARE procedure and their classification results are shown in table 3. The success ratio ranged from 94.1% for three variable model to 96.5% for 17 variable model. Increasing the number of independent variables beyond 10 variables did not improve the success ratio by much. A detailed discussion of the statistical analysis and the list of variables for each model can be found in Feng (1992).

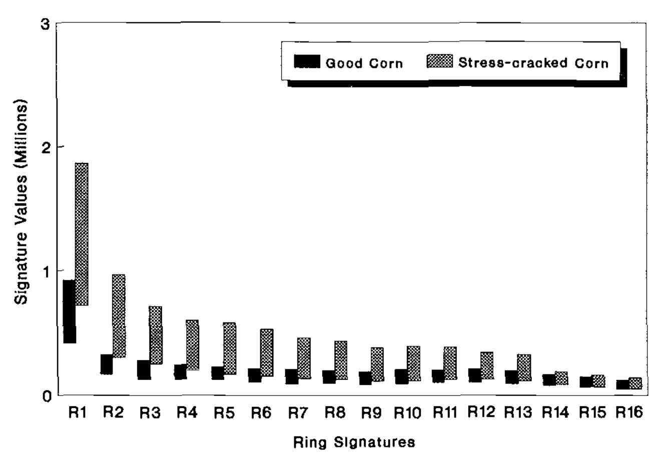


Figure 3–Range of ring values for good and stress-cracked corn kernels.

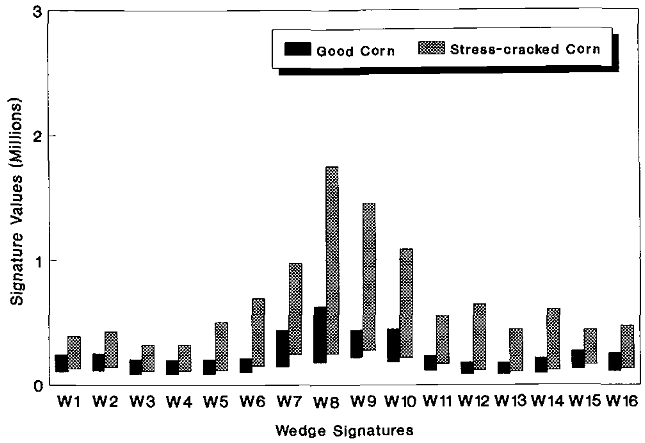


Figure 4–Range of wedge values for good and stress-cracked corn kernels.

When the STEPDISC and DISCRIM procedures were applied to Pioneer 3147 corn kernels, the success ratio reached 94.0% for good kernels and 98.5% for stress-cracked kernels with the average success ratio of 96.3%, as shown in table 4. The inspection result showed that, between Pioneer 3165 and Pioneer 3147, corn variety did not affect the classification performance of the image analysis procedure developed in this study.

The effect of image resolutions on the classification performance is summarized in table 5. The results showed that the 100 × 100 pixel resolution performed about the same as the 150 × 150 pixel resolution, but performance decreased rapidly as image resolution decreased beyond this point. When the pixel resolution was too low, it was even difficult to discern the stress cracks in kernels visually on the monitor. It was concluded that the 100 × 100 pixel resolution could be used to improve inspection speed without greatly losing system performance.

Summary and Conclusions

A corn kernel classification procedure was developed in the frequency domain using a two-dimensional Fourier Transform for inspection of stress cracks. Corn kernels were placed on a black background with a 0.5-mm aperture. Images of the kernels were acquired using back lighting. Contrast enhancement was performed followed by edge enhancement in order to improve stress crack recognition. An edge elimination algorithm was developed to remove unwanted edges of kernels while preserving the details of stress cracks. A FFT was applied to the pre-processed images, and the transformed images were condensed into 33 feature signatures representing position or orientation invariant morphological features. Two discriminant functions were used for stress crack inspection using 17 orientation invariant features and the following conclusions were made:

- The kernel classification procedure was able to detect stress cracks satisfactorily with an average success ratio of 96.4% for Pioneer 3165 corn kernels and 96.3% for Pioneer 3147 corn kernels.
- Between Pioneer 3165 and Pioneer 3147, corn hybrid did not affect the classification performance.

Table 1. Stepwise selection summary from procedure STEPDISC

Variable	F Statistic	Probability > F	Wilks' Lambda	Squared Partial Correlation Coefficient	Averaged Squared Canonical Correlation
R2	791.109	0.0001	0.2002	0.7998	0.7998
R13	13.435	0.0003	0.1874	0.0638	0.8126
DC	14.904	0.0002	0.1742	0.0707	0.8258
R7	8.401	0.0042	0.1670	0.0413	0.8330
R14	4.671	0.0319	0.1630	0.0235	0.8370
R15	10.699	0.0013	0.1545	0.0525	0.8455
R16	2.557	0.1114	0.1524	0.0131	0.8476

Table 2. Classification result by SAS procedure DISCRIM for Pioneer 3165

Class	No. of Samples	Correct Classification No.	Correct Classification %
Good	400	380	95.0
Stress-cracked	400	391	97.8
Total	800	771	96.4

Table 3. Percent correct classification ratio by various multiple regression models for Pioneer 3165

	Number of Independent Variables							
Class	1	3	4	5	7*	10	13	17
Good	90.3	92.3	92.5	93.8	94.3	94.8	94.8	95.3
Stress-cracked	98.5	96.0	98 3	97.5	97.8	97.8	97.8	97.8
Total	94.4	94.1	95.4	95.6	96.0	96.3	96.3	96.5

* This set of seven variables was the same set of variables as suggested y the procedure STEPDISC.

Table 4. Classification result by SAS procedure DISCRIM for Pioneer 3147

Class	No. of Samples	Correct Classification No.	Correct Classification %
Good	200	188	94.0
Stress-cracked	200	197	98.5
Total	400	385	96.3

Table 5. Effect of different resolution on the corn kernel classification performance

Resolution (pixels)	150 × 150	100 × 100	84 × 84	70 × 70	50 × 50	30 × 30
Average Success Ratio (%)	96.4	94.5	89.0	85.5	79.5	70.0

- Multiple regression analysis procedures performed as well as the SAS procedures, STEPDISC, and DISCRIM.
- A minimum pixel resolution of 100 × 100 is recommended to obtain optimum images for stress crack inspection.

References

Feng, Y. 1992. Frequency domain inspection of biological systems using Fourier Transform. Unpub. M.S. thesis, Clemson Univ., Clemson, S.C.

Gonzalez, R. C. and P. Wintz. 1987. *Digital Image Processing.* Reading, Mass.: Addison-Wesley Publishing Company, Inc.

Gunasekaran, S., S. S. Deshpande, M. R. Paulsen and G. C. Shove. 1985. Size characterization of stress cracks in corn kernels. *Transactions of the ASAE* 28(5):1668-1672.

Gunasekaran, S. and M. R. Paulsen. 1986. *Automatic Nondestructive Detective Testing*, vol. 12, 95-116. New York: Gordon and Breach Science Publishers.

Gunasekaran, S., M. R. Paulsen and G. C. Shove. 1986. A laser optical method for detecting corn kernel defects. *Transactions of the ASAE* 29(1):294-298, 304.

Gunasekaran, S., T. M. Cooper, A. G. Berlage and P. Krishnan. 1987. Image processing for stress cracks in corn kernels. *Transactions of the ASAE* 30(1):266-271.

Han, Y. J. and Y. Feng. 1994. Egg shell inspection using global image analysis. *Applied Engineering in Agriculture* 10(1):109-114.

Nussbaumer, H. J. 1982. *Fast Fourier Transform and Convolution Algorithms*. New York: Springer-Verlag, Berlin.

SAS User's Guide. 1985. Cary, N.C.: Statistical Analysis System Institute Inc.

Thompson, R. A. and G. H. Foster. 1963. Stress cracks and breakage in artificially dried corn. Marketing Research Rep. No. 631. October. Washington, D.C.: USDA, AMS, TFRD.