Paper No. 93-3526
An ASAE Meeting Presentation
UIUL-ENG 93-7012

3440

CORN KERNEL STRESS CRACK DETECTION BY MACHINE VISION

by

T. J. Yie — Graduate Research Assistant
K. Liao — Research Associate
M. R. Paulsen — Professor
J. F. Reid — Associate Professor
E. B. Maghirang — Visiting Researcher

Agricultural Engineering Department
University of Illinois
Urbana, IL

Written for presentation at the
1993 International Winter Meeting
sponsored by
ASAE

Hyatt Regency Chicago
Chicago, IL
Dec. 14-17, 1993

Summary:

A machine vision system was developed as a first step toward on-line stress crack detection in corn kernels. Stress cracks were determined by edge detection and preserved by outline edge elimination and noise reduction. The characteristics of stress cracks were represented by a feature vector. An on-line classifier was built to distinguish stress-cracked kernels from non-cracked kernels by a predefined discrimination function which was learned by the Learning Vector Quantization (LVQ) machine learning algorithm from training samples. The system achieved speeds of about two seconds per kernel and had accuracies ranging from 83 to 98%.

Keywords:
Corn, Machine Vision, Image processing, Nueral network, Classification, Quality control.

CORN KERNEL STRESS CRACK DETECTION BY MACHINE VISION[1]

T. J. Yie, K. Liao, M. R. Paulsen, J. F. Reid, and E. B. Maghirang

ABSTRACT

The ability to automatically detect stress cracks in corn in real time is an important factor for grain quality inspection. A machine vision system was developed as a first step toward on-line stress crack detection in corn kernels. Stress cracks were enhanced by edge detection and preserved by outline edge elimination and noise reduction. The characteristics of stress cracks were represented by a feature vector which included the mean, standard deviation and minimum distance along the x and y directions of an image profile. An on-line classifier was developed to distinguish stress-cracked kernels from non-cracked kernels by a discrimination function learned using the Learning Vector Quantization (LVQ) machine learning algorithm from training samples. Fourteen samples ranging from soft endosperm to hard endosperm kernels were tested. The system achieved speeds of about two seconds per kernel and had accuracies ranging from 80% to 100%. The system demonstrated potential for on-line grain quality inspection of stress cracks in corn.

INTRODUCTION

Corn is one of the most important cereal grains for domestic and export markets. Several kinds of damage may occur between the field and the consumer. Some defects are external and are easily detectable. Other defects, such as stress cracks, are internal and are induced by moisture gradients during drying and cooling. Stress cracks lie below the pericarp and some are not readily detectable. When stress-cracked corn is subsequently moved through the market channel, kernels with stress cracks break more easily than sound kernels resulting in generation of fine particles that lower the value of the corn. Currently, stress cracks are determined by human inspection on small-scale samples or are not tested at all due to the time consuming nature of the tests. In order to identify and market excellent corn quality for high valued markets such as snack food processing, wet milling and dry milling, an automatic inspection system for stress crack detection is needed.

---

[1]Acknowledgements: This study was a part of Project No. 55030 and 52802 of the Illinois Agricultural Experiment Station, College of Agriculture, University of Illinois at Urbana-Champaign. The research was supported in part by the Federal Grain Inspection Service, USDA.

Several nondestructive testing techniques have been explored for an automated grain quality inspection system. Gunasekaran et al. (1986) used light reflectance measurements with a laser beam to detect external defects, but the technique was found insufficient for stress crack detection. Ultrasonic imaging was also found to be unsuitable since intercellular air spaces in the kernel blocked the wave transmission (Gunasekaran and Paulsen, 1986; Gunasekaran et al., 1987). Machine vision has been widely used for inspection of agricultural products. Gunasekaran et al. (1987) reported that backlighting corn kernels produced a high contrast across the stress cracks and developed an image processing algorithm to detect stress cracks. Their system could detect 90% of the stress cracks and it was reported that the corn kernels had to be carefully positioned to obtain usable images. However, no discrimination function was developed to classify the processed image.

Han et al. (1992) used the frequency domain for stress crack detection. A two-dimensional Fast Fourier Transform (FFT) was applied to preprocessed corn images and some stress crack related frequency features were selected. For preserving the details of stress cracks, the edge outline was eliminated before the frequency transformation. The image classification procedure achieved an average success ratio above 96% for the two varieties tested. The discrimination process was accomplished by multiple regression analysis and SAS procedures, which were not on-line procedures.

Reid et al. (1991) developed a machine algorithm vision for detection of corn stress cracks. The algorithm achieved an average accuracy of 77% with a processing speed of about 80 seconds per kernel, obviously too slow for an on-line grain inspection system. In order to design an on-line system, the processing speed had to be increased. This can be done by using image processing hardware now available and by designing an algorithm to use local on-board operations instead of operations written in software.

OBJECTIVE

The objective of this research was to develop a high-speed, accurate algorithm suitable for on-line detection of stress cracks in corn.

STRESS CRACK DETECTION ALGORITHM

A stress crack detection algorithm was developed for stationary kernels that included the following steps: (1) image processing; (2) feature extraction; and (3) on-line classification. Image processing was first performed to detect possible stress cracks in the corn kernel. Stress crack related features were then extracted from the processed image profile, which was calculated from the processed image. Stress crack classification was accomplished by building an on-line classifier which was obtained by training, testing, and using the Learning Vector Quantization (LVQ) machine learning algorithm.

Image Processing

The image of a corn kernel was acquired and saved in a frame buffer of the image processing board. The red component of the image provided the most stress crack-related information and was processed for possible stress crack detection. Image processing included the following steps: (1) defining the region of interest (ROI); (2) performing an edge detection; (3) thinning of edges in the ROI; and (4) eliminating the outline edge.

An ROI was defined to exclude tip cap and crown areas of a kernel. From a backlighting source, the tip cap surface was observed to be highly textured and found to give noisy edges. The dark crown area produced a similar effect. Stress cracks in both tip cap and dark crown areas were rarely observed. Gunasekaran et al. (1986) reported that stress cracks start at the center of the kernel and extend toward the periphery underneath the pericarp. Thus, there was rarely any information lost by eliminating the tip cap and crown end. The edge formed by the kernel boundary was not related to the stress cracks so it was also removed.

For creating the ROI mask, the corn kernel was segmented from its background by thresholding the image. The axis of symmetry, the position and length of the major and minor axes were calculated from the binary image. Tip cap and crown regions were located from the calculated shape parameters. The ROI was then defined by a mask which eliminated certain areas from the tip cap and crown ends (Figure 1). All the following operations were done inside the ROI mask.

The edges of the corn kernel including possible stress cracks were detected by an edge operator. Several operators including the Sobel, Prewitt and Kirsch operator were tested. The Kirsch operator, which provided strong edges, was selected for edge detection on the red component image. The Kirsch edge operators used were:

$$\begin{bmatrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix} \quad \begin{bmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix} \quad \begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix} \quad \begin{bmatrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{bmatrix}$$

Edge detection was performed by the convolution of the four 3 x 3 Kirsch edge detection filters on the ROI. Edge pixels representing stress cracks were connected groups of pixels. Isolated pixels represented noise edges. The detected edges were eroded to only one pixel in width using skeleton thinning to strengthen the stress crack signal and to reduce the effect of noise edges.

The boundary edge of the ROI was eliminated by erosion of the ROI for a five-pixel wide distance toward the corn kernel center. The remaining ROI contained only stress crack-related edges and some noise.

Feature Extraction

The x and y profiles of the processed image were generated and saved in look-up tables on the image board. Stress crack-related features were then calculated from these x and y profiles to form a six-dimensional feature vector. The six features, the mean values of x and y profiles, their standard deviations, and the widths of the non-zero signal in the x and y profiles, were chosen to represent the characteristics of the stress cracks based on previous experimental results. The values of means, standard deviations and the widths of occupied stress crack signals would be larger if stress cracked edges were present in the profile.

A search procedure was performed along the x and y profiles to find the minimum length occupied by the image signal. The search started from one end of the x-directional profile until at least three pixels connected together were found. Any single- or two-connected pixels were considered as noise. The position p1 was considered as one end of the stress crack signal. The same search was done from the other end and the position p2, where the search stopped, was recorded as the other end point of the stress crack signal. The distance between p1 and p2 was the width of the image signal. The same procedure was done for the y-directional profile.

Stress Crack Classification

Different pattern recognition methods have been widely used to classify image processing results. Kohonen (1990) presented a Learning Vector Quantization (LVQ) machine learning algorithm for the discrimination and classification of high dimensional signal. LVQ has been successfully used in speech recognition and digital communication. Liao et al. (1992) used an LVQ machine learning algorithm to classify a six-dimensional multi-spectral corn color signal. LVQ is used to build a classification function from training samples by forming a codebook. Multidimensional feature vectors of training samples were mapped into a finite number of vectors with each corresponding to a certain category. The finite number of vectors were called the codebook and each vector was called a codebook vector. Several codebook vectors were assigned to represent the same category and each codebook vector was labeled with its corresponding category name.

The LVQ machine learning algorithm used by Liao et al. (1992) was used in this study. A classification function was built based on 31 non-cracked kernels and 29 stress cracked kernels. Feature vectors of the training samples were calculated and used to determine codebook vectors. The codebook contained 40 vectors with a label of stress crack status associated with each of them. The classification function was formed by comparing an unclassified input stress crack-related feature vector with all the codebook vectors, the status of codebook vector which had the minimum distance with the input vector was assigned to be the category of input vector.

In order to speed up the classification, the codebook was used to build a comparison procedure in software to simulate the pre-defined stress crack discriminant function. An on-line classifier based on this classification function was incorporated with the image processing and feature extraction parts described previously.

Overall, the stress cracks detection algorithm steps are summarized as:

A. Image processing
   1. Acquire a corn kernel image;
   2. Define ROI for stress crack detection;
      2.1 binarize the original image;
      2.2 calculate the center, major and minor axes of the corn kernel;
      2.3 locate positions of tip cap and crown regions;
      2.4 cut off non-essential tip cap and crown regions;
   3. Perform Kirsch edge detection in the ROI;
   4. Perform skeleton thinning on the detected edges;
   5. Remove the boundary edge;

B. Feature extraction
   1. Generate the x and y profiles of the ROI;
   2. Calculate the stress crack features from x and y profiles;

C. Stress crack classification
   1. Form a discriminant function by training LVQ;
   2. Build an on-line classifier in software;
   3. Use the classifier.

EQUIPMENT AND TEST PROCEDURE

Image Acquisition

Image System. A laboratory setup was devised to allow experimentation with lighting, imaging and the algorithm for corn kernel stress crack detection (Figure 2). The setup allowed individual kernels to be placed manually under the camera for imaging. A SONY Model XC-711 CCD RGB 768(H) x 493(v) color camera[2] was used to grab RGB images of kernels. The distance between object and the camera was about 37 cm and the camera lens MICRO-NIKON 55 mm aperture was set at 5.6. Since the intended application of this research was to build a real-time grain quality inspection system, speed was a critical consideration in system design and algorithm development. A Matrox Electronic Systems Ltd. Model Image-1280 real-time image processing board was used to perform the basic image processing operations. The algorithm was written in C and run on a Compaq 386/33 PC running the DOS version 6.0 and Microsoft C version 6.0.

---

[2]Mention of trade names, proprietary product or specific equipment or company in this paper is solely for the purpose of providing specific information and does not consist a guarantee or warranty by the University of Illinois and does not imply approval of the name product to the exclusion of other products that may be suitable.

Illumination. Stress cracks are internal fissures in kernel endosperm and are not readily identifiable without special lighting. Gunasekaran et al. (1986) previously found that back lighting was more suitable than front lighting for stress crack detection. In this study, stress crack illumination was performed using back lighting. Corn kernels were placed with the germ side down on a smoky glass plate which was illuminated by one GE EYE 75W quartz halogen bulb operated at 9.0 volt DC. The angle between the direction of the bulb light and the smoky glass plate was about 45°, and the major axis of kernels were perpendicular to the direction of the bulb light (Figure 2). It was observed that the acquired images had stronger edges whenever the direction of the light was perpendicular to the direction of the stress cracks. The distance from the bulb to the sample was about 65 mm.

Experimental Test

Three inspection procedures were evaluated, namely: (1) human inspection; (2) image inspection from the monitor; and (3) machine vision. Human inspection, which is considered as the control, involves manually checking the corn kernel on a light table. Image inspection involves human inspection of the corn kernel image on the monitor for stress cracks. This allows for an evaluation of the true performance of the vision algorithm when operated on discernable images. The machine vision system involves manual placement of the corn kernel and identification of stress cracks by the system.

Statistical Analysis

The number of kernels required for inspection was obtained using a comparison of stress crack percentages at different kernel quantities (10, 20, 50, 100, 150, 200 and 300 kernels). Likewise, the Stein's two-stage sample procedure (Steel and Torrie, 1980) was used to estimate the sample size required for stress crack inspection. Three varieties representing different levels of stress crack percentages were used in the test.

To test the repeatability of results, an indicator of procedure accuracy, the same sets of corn kernels were inspected for stress cracks ten times. A comparison of the number of kernels classified as uncracked and as stress cracked was done.

A comparison of the three inspection procedures was done using the Duncan Multiple Range Test (DMRT). To determine the system accuracy, the machine vision system performance was compared with that of human inspection and image inspection from the monitor using an F-test. Also, a comparison of the accuracy of the system when used for soft and hard endosperm corn kernels was done. Samples were grouped based on the 100-kernel densities where, group 1 consisted of samples with 100-kernel density less than or equal to 1.20 g/cm^3, while group 2 included samples with 100-kernel density greater than 1.20 g/cm^3.

RESULTS AND DISCUSSION

Sample Size Estimation

It was assumed that the human inspection method based on 300 kernels would best represent the actual percentage of stress cracks in each sample. Therefore, sample 911 had 150/300 or 50% stress cracks; sample 416 had 145/300 or 48.3% stress cracks; and sample FR1141 X FR36 had 157/300 or 52.3% stress cracks (Table 1). In Figure 3, it can be visually observed that for the three samples analyzed, the percentages of stress cracks remained relatively constant from 50 kernels to 300 kernels inspected. This information provided a basis for concluding that using 50 kernels will give the percentage of stress cracks representative of a sample and that further increasing the number of kernels will give the same result.

To confirm this visual observation, the Stein's two-stage sample procedure was used in estimating the number of observations necessary for obtaining the percentages of stress cracks of a sample (Steel and Torrie, 1980). For each stress crack inspection technique, the variances in the transformed data were first estimated then the total number of observations necessary were computed. Assuming a 95% confidence interval, the Stein's two-stage test showed that a sample size of 50 kernels was adequate in the estimation of percentages of stress cracks in a sample.

Repeatability of the Inspection Methods

The same 50 kernels were tested ten times to provide an indication of the repeatability of the image inspection and machine vision inspection methods. Three samples representing different levels of stress cracks were tested. Sample 1 had a relatively low stress crack level. Sample 2 had a relatively high stress crack level; and sample 3 had a relatively low stress crack level but some kernels had stress cracks only on their side edges. For each of the ten tests, the kernels were tested in groups of 50 kernels, and thus were picked up and repositioned for each test.

The test results showing the number of kernels found with stress cracks are shown in Table 2. All tests used 50 kernels as the sample size. For sample 1, the human inspector found stress cracks ranging from 12 to 14 kernels. The human inspection of the monitor found stress cracks of 11 to 15 kernels and the machine vision system found stress cracks of 12 to 17 kernels. For sample 2, the human inspector found stress cracks ranging from 41 to 43 kernels. The human inspection of the monitor found stress cracks ranging from 40 to 43 kernels, and the machine vision system also found 40 to 43 kernels with stress cracks. For sample 3, the human inspector found stress cracks ranging from 11 to 14 kernels. The human inspection of the monitor found stress cracks ranging from 10 to 16 kernels, and the machine vision system found 13 to 20 kernels.

For all three samples tested, human inspection gave the lowest standard deviation followed by image inspection then machine vision (Table 3). This implies that human inspection, which is considered as the control, has the best repeatability among the procedures evaluated. Considering that the difference in standard deviation between inspection procedures within samples were relatively small, this confirms that both image and machine vision inspections are repeatable.

Sample 3 consistently showed higher standard deviations than both samples 1 and 2 for all inspection procedures. This pointed out that detection of stress cracks were not only affected by the inspection procedure but also by the inherent nature of the sample. There are samples where detection of stress cracks can be more difficult. An example of this inherent characteristic that made stress crack detection difficult was the presence of stress cracks near the outer edges of the kernels.

System Accuracy

Fourteen corn samples, four of which were obtained from a snack food processor and ten harvested from an experimental plot in Illinois then dried using different drying temperatures as specified and stored for almost eight months in a 40°C chamber were used in evaluating three stress crack inspection procedures. The moisture contents at which the samples were obtained were not altered.

Table 4 presents the mean number of kernels based on three replicates, which were found to have stress cracks based on human inspection, image inspection and machine vision. Depending on the variety, the number of stress cracks out of 50 kernels inspected varied from 9 to 50 based on human inspection; 7 to 47 based on image inspection; and 8 to 44 based on machine vision. The Duncan Multiple Range Test (DMRT) showed that from the 14 varieties inspected, the number of kernels classified to have stress cracks in eight varieties were not significantly different regardless of inspection procedure used. In four other varieties, human inspection and image inspection results were not significantly different; and even when the human inspection and machine vision results were significantly different, the image inspection and machine vision results were not significantly different. There was one variety where human inspection and image inspection procedures were not significantly different in the evaluation of stress cracks but were both significantly higher from that of the results using machine vision. Another variety had a significantly different number of stress cracks with differences in inspection method. Generally, human inspection gave the highest number of kernels identified to have stress cracks, followed by image inspection then by machine vision.

The machine vision system accuracy was compared to human inspection and image inspection. The results are presented in Table 5. The system accuracy was determined as a percentage of the number of kernels classified by the machine vision system with the same result as the human inspector. While a human inspector can find stress cracks on the side by viewing from different angles, the machine vision system acquires and processes only the top view of the corn kernel image. Thus, there are some kernels with faint side stress cracks which a human inspector can see but are missed by the machine vision system. Another accuracy evaluation was then considered, wherein the image of the kernel on the monitor was inspected by a human inspector. This gave the true accuracy of the vision algorithm when operated on discernible images.

The system accuracy compared to human inspection ranged from 83 to 95%; and compared to image inspection on the monitor ranged from 87 to 98% (Table 5). The lower system accuracy when compared to human inspection than to image inspection may be explained by the inability of the machine vision algorithm to find stress cracks that do not appear on the monitor. An F-test proved that machine vision accuracies were significantly higher when compared to the monitor image inspection than to human inspection.

A factor that was observed to affect the system accuracy was the true density of the corn sample. The 14 samples were grouped into two with the first group (G1) consisting of seven samples with 100-kernel densities of 1.20 g/cm^3 or less and the second group (G2) consisting of seven samples with 100-kernel densities greater than 1.20 g/cm^3. The F-test showed that G1 had significantly lower system accuracies than G2 for both system accuracies compared to human inspection and image inspection. This implies that stress cracks are more easily viewed in hard endosperm samples than in soft endosperm samples.

System Speed

The system used a total of about two seconds per kernel to acquire an image and give a classification result, regardless of whether the kernel was sound or stress cracked. Of this time, about one second of computer time was used to locate and eliminate the tip cap and crown areas.

CONCLUSIONS

A machine vision algorithm was developed for inspection of stress cracks in corn. Based on the red component image grabbed by the RGB color camera, the image processing algorithm and classifier provided a successful detection of stress cracks ranging from 83% to 98%. The processing time for each kernel was less than two seconds from the live image to the final classification result. The system demonstrated potential for on-line grain quality inspection of stress cracks in corn.

REFERENCES

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

Gunasekaran, S. and M. R. Paulsen. 1986. Automatic, nondestructive detection of corn kernel defects. *International advances in nondestructive testing*. Vol 12, Gordon and Breach Science Publishers. NY. pp 95-116.

Gunasekaran, S., T. M. Cooper, A. G. Berlage, and P. Krishnan. 1987. Image processing for stress cracks in corn kernels. *Transactions of ASAE* 30(1):266-270.

Han, Y. J., Yi Feng, and C. L. Weller. 1992. Frequency domain inspection of corn kernel stress-cracks. ASAE Paper No. 92-7018. American Society of Agricultural Engineers, St. Joseph, MI.

Kohonen, T. K. 1990. The self-organizing map. *Proceedings of the IEEE* 78(9):1464-1480.

Liao, K., Zhiwei Li, J. F. Reid, M. R. Paulsen and Bingcheng Ni. 1992. Knowledge-based color discrimination of corn kernels. ASAE Paper No. 92-3579. American Society of Agricultural Engineers, St. Joseph, MI.

Reid, J. F., C. Kim, and M. R. Paulsen. 1991. Computer vision sensing of stress cracks in corn kernels. *Transactions of ASAE* 34(5):2236-2244.

Steel, R.G.D. and J. H. Torrie. 1980. *Principles and Procedures of Statistics: A Biometrical Approach*. McGraw Hill Book Co., Inc.

Table 1. Number of stress cracked kernels for three corn varieties at different sample sizes using three inspection techniques as a procedure for estimating sample size needed.

SAMPLE ID	INSPECTION PROCEDURE	NUMBER OF KERNELS WITH STRESS CRACKS [1]						
		10[2]	20	50	100	150	200	300
911 (13.6)[3]	Human	4	9	25	52	73	96	150
	Image	4	11	27	54	77	101	157
	Machine Vision	4	10	25	53	77	101	156
416 (14.2)	Human	2	6	22	46	65	91	145
	Image	2	6	23	46	67	94	147
	Machine Vision	2	8	26	50	73	101	160
FR1141 x FR36 (13.8)	Human	8	13	28	52	80	102	157
	Image	7	13	29	53	78	101	155
	Machine Vision	8	14	30	54	81	105	160

[1]Number of good kernels = Number of kernels inspected - Number of kernels with stress cracks.
[2]Number of kernels inspected.
[3]Figures in parentheses are moisture content of sample, % wet basis.

Table 2. Number of corn kernels with stress cracks when 50 kernels were tested ten times for three corn samples as a procedure for evaluating repeatability of inspection results.

Sample No.[1]	INSPECTION PROCEDURE	NUMBER OF CORN KERNELS WITH STRESS CRACKS[2]									
		1	2	3	4	5	6	7	8	9	10
1	Human	12	13	13	13	12	14	14	13	12	12
	Image	15	11	13	13	14	14	14	14	15	12
	Machine Vision	15	12	15	13	16	15	17	16	17	16
2	Human	42	41	43	42	42	41	42	41	42	42
	Image	42	40	41	43	42	42	42	42	43	42
	Machine Vision	40	42	40	40	42	43	43	40	42	41
3	Human	11	13	13	13	12	14	14	13	12	12
	Image	11	16	11	12	12	11	13	13	10	13
	Machine Vision	15	20	16	17	15	14	13	20	14	19

[1]Sample Nos. 1, 2, and 3 refers to samples identified as 426 low-stress crack level, 912 high-stress crack level and FR1087 x LH123, respectively.
[2]Number of good kernels = 50 kernels - Number of kernels with stress cracks.

Table 3. Mean percentages of stress cracks and standard deviations for ten tests of 50 kernels for three corn samples.

INSPECTION PROCEDURE	MEAN PERCENTAGE OF STRESS CRACKS		
	Sample 1	Sample 2	Sample 3
Human Inspection	26 (1.5)[1]	84 (1.2)	26 (1.8)
Image Inspection	27 (2.4)	84 (1.7)	24 (3.2)
Machine Vision	30 (3.1)	83 (2.3)	32 (4.9)

[1]Figures in parentheses are standard deviations.

Table 4. Machine vision stress crack detection accuracy for three replicates of 14 corn samples compared to human inspection and image inspection from the monitor.

VARIETY	MOISTURE CONTENT, %wb	NUMBER OF CORN KERNELS WITH STRESS CRACKS*		
		Human Inspection	Image Inspection	Machine Vision
FR618 x LH123 (80°C - drying temp)	12.1	35.00[a] (2.65)**	34.00[a] (2.65)	35.67[a] (0.58)
FR27 x FRMo17 (110°C - drying temp)	10.4	46.00[a] (2.00)	45.33[ab] (2.52)	41.67[b] (1.53)
FR1141 x FR36 (110°C - drying temp)	12.0	39.33[a] (2.08)	36.00[ab] (1.73)	34.33[b] (3.06)
FR1141 x FR36 (80°C - drying temp)	13.1	40.00[a] (2.65)	37.33[a] (0.58)	33.67[b] (1.15)
FR27 x FRMo17 (50°C - drying temp)	11.4	40.33[a] (3.21)	38.33[ab] (1.53)	35.67[b] (1.53)
FR1141 x FR36 (ambient air dried)	13.8	32.33[a] (2.08)	30.00[ab] (1.73)	26.67[b] (1.15)
FR27 x FRMo17 (ambient air dried)	10.7	16.00[a] (6.00)	14.33[a] (5.03)	14.33[a] (3.79)
FR1087 x LH123 (50°C - drying temp)	10.7	49.67[a] (0.58)	47.33[b] (0.58)	44.33[c] (1.15)
FR618 x FR600 (ambient air dried)	10.8	37.00[a] (1.00)	35.33[a] (1.15)	35.67[a] (1.53)
416 med low stress crack level	14.2	21.67[a] (3.51)	18.33[a] (1.15)	17.33[a] (1.53)
912 high stress crack level	13.6	41.33[a] (1.53)	39.67[a] (2.31)	38.67[a] (1.53)
FR1087 x LH123 (ambient air dried)	11.8	9.00[a] (6.25)	7.33[a] (5.77)	7.67[a] (4.04)
911 med high stress crack level	13.6	20.67[a] (2.89)	20.33[a] (2.31)	19.67[a] (2.52)
426 low stress crack level	14.2	13.00[a] (1.73)	11.33[a] (1.53)	10.33[a] (0.58)

*Row means with the same superscript are not significantly different at the 5% probability level.
**Figures in parentheses are standard deviations of three replications.

Table 5. Machine vision stress crack detection accuracy for three replicates of 14 corn samples compared to human inspection and image inspection from the monitor.

VARIETY	100-KERNEL DENSITY[1], g/cm³	MACHINE VISION SYSTEM ACCURACY, % compared to	
		Human Inspection	Image Inspection
FR618 x LH123 (80°C - drying temp)	1.15	85.33 (5.03)[2]	87.33 (5.03)
FR27 x FRMo17 (110°C - drying temp)	1.16	88.67 (4.16)	90.00 (4.00)
FR1141 x FR36 (110°C - drying temp)	1.17	88.67 (7.02)	95.33 (1.15)
FR1141 x FR36 (80°C - drying temp)	1.18	87.33 (6.43)	92.67 (1.15)
FR27 x FRMo17 (50°C - drying temp)	1.19	82.67 (2.31)	86.67 (4.62)
FR1141 x FR36 (ambient air dried)	1.19	87.33 (5.03)	92.67 (1.15)
FR27 x FRMo17 (ambient air dried)	1.20	91.33 (1.15)	93.33 (1.15)
FR1087 x LH123 (50°C - drying temp)	1.25	90.00 (2.00)	94.00 (2.00)
FR618 x FR600 (ambient air dried)	1.26	94.67 (5.03)	98.00 (3.46)
416 med low stress crack level	1.27	88.67 (4.16)	95.33 (1.15)
912 high stress crack level	1.28	94.67 (1.15)	98.00 (2.00)
FR1087 x LH123 (ambient air dried)	1.28	90.00 (5.29)	91.33 (5.03)
911 med high stress crack level	1.29	95.33 (1.15)	96.00 (2.00)
426 low stress crack level	1.29	93.33 (2.31)	96.67 (2.31)

[1]Values are means of three replicates and were obtained at the moisture level presented in Table 4.
[2]Figures in parentheses are standard deviations of three replications.

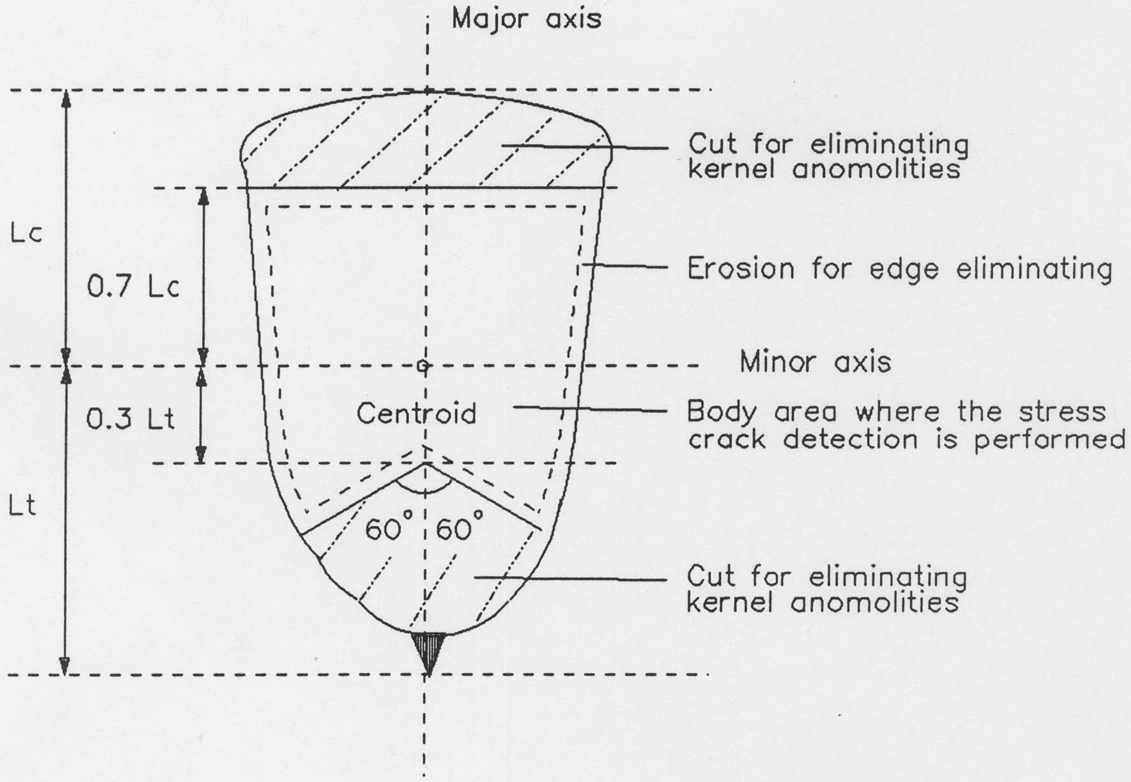

Figure 1. Region defined on the corn kernel for stress crack detection (L_c = crown side length and L_t = tip cap side length).

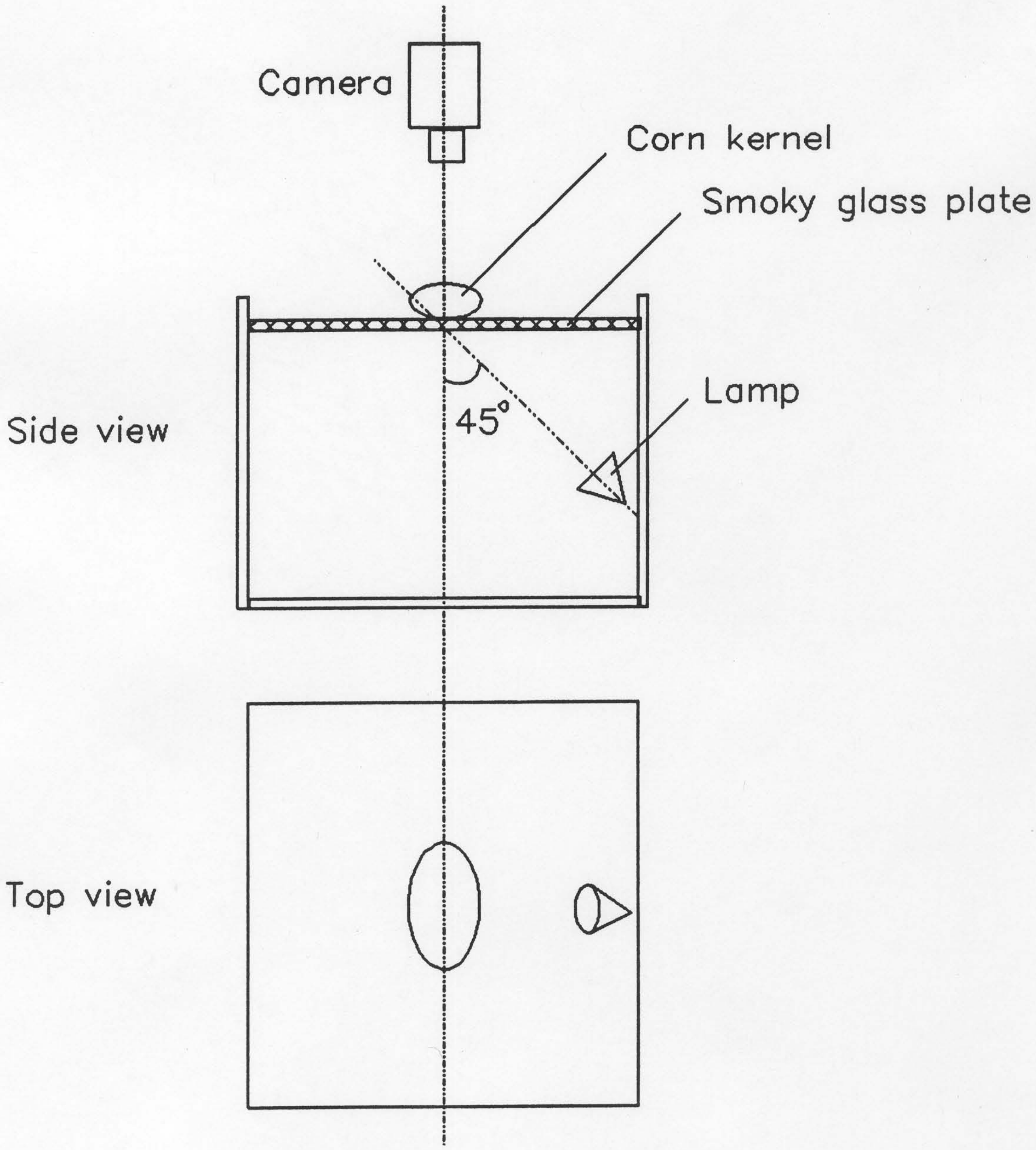

Figure 2. Lighting source and corn kernel placement for stress crack detection.

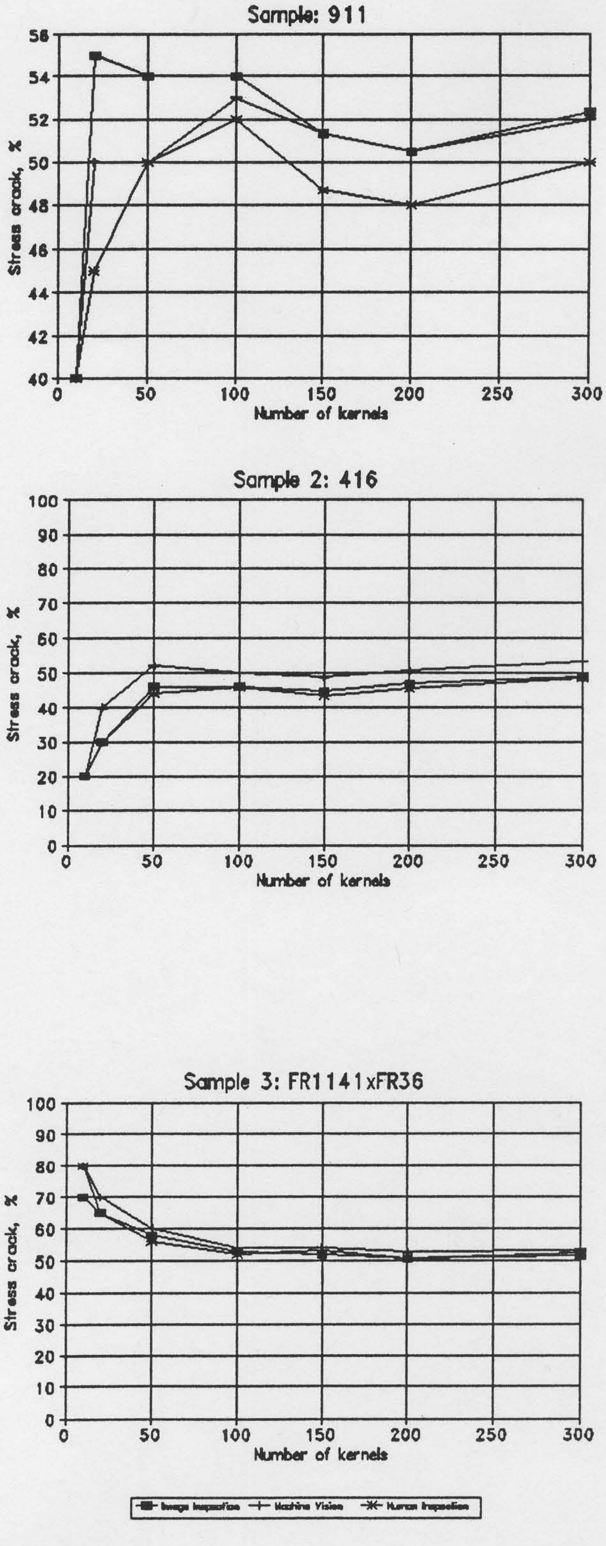

Figure 3. Number of stress cracked kernels for three corn varieties at different sample sizes using three inspection techniques as a procedure for estimating sample size needed.