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Abstract

A computer vision system was developed for evaluation of the total damage factor used in corn grading. Major categories of corn damage in the Midwestern U.S. grain market were blue–eye mold damage and germ damage. Seven hundred twenty kernels were obtained from officially sampled Federal Grain Inspection Service (FGIS) corn samples and classified by inspectors on the Board of Appeals and Review. Inspectors classified these kernels into blue–eye mold, germ–damaged, and sound kernels at an 88% agreement rate. A color vision system and lighting chamber were developed to capture replicate images from each sample kernel. Images were segmented via input of red, green, and blue (RGB) values into a neural network trained to recognize color patterns of blue–eye mold, germ damage, sound germ, shadow in sound germ, hard starch, and soft starch. Morphological features (area and number of occurrences) from each of these color group areas were input to a genetic–based probabilistic neural network for computer vision image classification of kernels into blue–eye mold, germ damage, and sound categories. Correct classification by the network on unseen images was 78, 94, and 93%, respectively. Correct classification for sound and damaged categories on unseen images was 92 and 93%, respectively.

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ABSTRACT. *A computer vision system was developed for evaluation of the total damage factor used in corn grading. Major categories of corn damage in the Midwestern U.S. grain market were blue–eye mold damage and germ damage. Seven hundred twenty kernels were obtained from officially sampled Federal Grain Inspection Service (FGIS) corn samples and classified by inspectors on the Board of Appeals and Review. Inspectors classified these kernels into blue–eye mold, germ–damaged, and sound kernels at an 88% agreement rate. A color vision system and lighting chamber were developed to capture replicate images from each sample kernel. Images were segmented via input of red, green, and blue (RGB) values into a neural network trained to recognize color patterns of blue–eye mold, germ damage, sound germ, shadow in sound germ, hard starch, and soft starch. Morphological features (area and number of occurrences) from each of these color group areas were input to a genetic–based probabilistic neural network for computer vision image classification of kernels into blue–eye mold, germ damage, and sound categories. Correct classification by the network on unseen images was 78, 94, and 93%, respectively. Correct classification for sound and damaged categories on unseen images was 92 and 93%, respectively.*

Keywords. *Grain damage, Evaluation, Machine vision, Probabilistic, Neural network, Corn, Color, Pattern recognition.*

S teenhoek et al. (2001) developed a method for segmentation of areas representing damaged and sound features within corn kernel images. In this article, that method is incorporated into a system for machine vision evaluation of corn damage.

The total damage factor in corn is one of the inspection factors used to determine corn grades in the United States as corn with damaged kernels has lower end–use value and a shorter storage life than undamaged corn. Damaged kernels and their accurate measurement is a problem for the corn industry because measurements are based on visual assessment and can be quite subjective and inconsistent (Wilcke et al., 1993). The process is laborious and time–consuming. Use of machine vision is a proposed aid to remove subjectivity in determination of the corn kernel damage factor.

Damaged kernels are defined as "kernels and pieces of corn kernels that are badly ground–damaged, badly weather–damaged, diseased, frost–damaged, germ–dam- aged, heat–damaged, insect–bored, mold–damaged, sprout– damaged, or otherwise materially damaged" (Federal Grain Inspection Service, 1997). Sound kernels are defined as those free from any of the designated types of damage. For U.S. grade numbers 1, 2, 3, 4, and 5, the percentage of total damaged kernels is limited to 3, 5, 7, 10, and 15%, respectively.

A detailed description of the overall corn grading process is given in FGIS (1997) and Steenhoek (1999). For evaluation of the damaged kernel grade component, each kernel in a 250–g sample is individually examined for damage by comparing its visual appearance with interpretive line slides (slide film photos representing different types of damage). Damage, as indicated by the interpretive line slides, is identified by discolorations or changes in kernel appearance. Each interpretive line slide shows the level of discoloration or deterioration for a kernel to be considered damaged.

The literature reports several applications of machine vision in analysis of grains and other agricultural products. Ng et al. (1998) used neural network techniques to segment corn kernel images into mold and nonmold categories and then calculate mold coverage by area ratios. The system provided results that were more repeatable than human measurements. A machine vision–based corn kernel inspection system developed by Ni et al. (1993) incorporated a neural network classifier using morphological features to successfully discriminate between whole and broken corn kernels. Zayas and Walker (1995) identified broken and sound corn kernels with multispectral image analysis techniques. Pixels representing endosperm and sound tissue were collected and used for image segmentation. A 100% correct recognition rate of broken and sound kernels was achieved. Tetrazolium staining for evaluation of seed corn quality was measured using machine vision systems developed by Howarth and Stanwood (1992) and Xie and

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Paulsen (1997). Liu and Paulsen (1997) developed a definition of corn whiteness based on YcrCb color coordinates to allow a machine vision system to differentiate between yellow and white corn. The algorithm was able to differentiate among color differences noticeable by human perception. Shatadal et al. (1998) used a neural network classifier to distinguish grayscale images of vitreous and nonvitreous wheat kernels by identifying area ratios of gray–level windows across an 8–bit imaging range. Majumdar et al. (1997) used digital image analysis algorithms to classify wheat, barley, oats, and rye using color and textural features. Morphological features and pixel value statistics provided inputs to a neural network classification scheme developed by Winter et al. (1997) to predict the popability of popcorn kernels. Accuracy of the system in determining if a kernel would pop was 75%.

SURVEY OF CORN KERNEL DAMAGE

During preliminary discussions with corn damage inspection experts, it was recurrently suggested that most corn kernel damage seen in Midwestern U.S. growing regions was due to either germ or blue–eye mold damage. Furthermore, it was suggested that corn kernel damage usually occurred in the germ area and on the germ side of the kernel surface.

To confirm this hypothesis, a survey questionnaire was submitted to six corn inspection experts on the U.S. Federal Grain Inspection Service Board of Appeals and Review (table 1). These individuals have many years of experience in corn grading and are considered the final authority in all U.S. grain inspection matters. The survey questionnaire asked each expert to estimate, "the frequency of occurrence of each FGIS interpretive line slide damage class as a percentage of total damaged kernels."

This survey confirmed preliminary investigations and suggested that about 90% of all damaged corn kernels in the Midwestern U.S. corn market could be classified into either germ–damaged or blue–eye mold–damaged categories. Therefore, development of a machine vision system that could be trained to recognize sound kernels, germ–damaged kernels, and blue–eye mold–damaged kernels would contribute significantly to automated corn kernel damage inspection.

OBJECTIVES

The primary objective of this study was to develop a computer vision system to capture corn kernel images and to classify the images into categories of sound and damaged (germ–damaged and blue–eye mold–damaged). A secondary objective was to compare the accuracy and repeatability of the developed system to the accuracy and repeatability of human inspection.

MATERIALS AND METHODS
CORN SAMPLES

Samples of sound, blue–eye mold–damaged, and germ–damaged kernels were handpicked from 24 random grain lots using official FGIS sampling procedures. For each

Table 1. Classes of corn damage most frequently seen by FGIS inspectors.[a]

Type of Damage	Inspector No.						Avg.
	1	2	3	4	5	6	
Germ damage	85	90	30	60	80	78.7	70.6
Blue–eye mold damage	5	4	30	39.3	18	20	19.4
Mold damage	5	4	10	0.3	0.5	0.1	3.3
Cob rot damage	2	1	3	0.2	1	1	1.4
Heat damage(respiration)	1	1	5	0.1	0.1	0.1	1.2
Insect damage	2		4	0.1	0.2	0.1	1.1
Sprout damage			3		0.1		0.5
Surface mold (more than slight)			3		0.1		0.5
Drier damage			3				0.5
Heat damage (drier)			3				0.5
Pink epicoccum			3				0.5
Surface mold (blight)			3				0.5
Total	100	100	100	100	100	100	

[a] Response from survey question "Listed below are the classes of corn kernel damage categorized by the Federal Grain Inspection Service inter-pretive line slides. In your opinion, please estimate the frequency of oc-currence for each damage class as a percentage (i.e. — of all the damaged kernels which would be picked from a sample, what percentage would be in each class?)." Each inspector was on the FGIS Board of Appeals and Review.

lot, an inspector on the FGIS Board of Appeals and Review selected 10 sound kernels, 10 blue–eye mold–damaged kernels, and 10 germ–damaged kernels. The total number of kernels selected was 720 (24 sets × 3 classes × 10 kernels per class). Each of the 720 kernels was assigned a randomly generated kernel identification code and placed in an individual plastic bag.

An experiment was performed to verify the classification of each of the corn kernel samples. All 720 kernels were inspected in a random order by four FGIS inspectors. The inspectors were instructed to assign the following kernel categories: sound kernel, germ–damaged kernel, and blue–eye mold–damaged kernel.

COLOR VISION SYSTEM

A color vision system was chosen for this study. Our early experiments suggested that gray–level differences in standard monochrome cameras were unsuitable for kernel damage identification. Similar gray levels can occur between kernel areas, and the natural curvature of the kernel surface greatly affects homogeneity of the gray–level intensity. The boundary separating damaged areas depends on contrast and was not clear in gray–level images. Color vision systems provide multiple layers of information that can be used to improve image segmentation and boundary delineation.

An image processing system developed by Sharp Digital Information Products (Sharp Digital Information Products, 1996) was used in this study. Components, as illustrated in figure 1, are (1) a Pentium computer with Windows 95 operating system, (2) a frame processor board to capture, process, and display images, (3) a color camera, (4) an image acquisition chamber, (5) a monitor to display of images, and (6) a user interface monitor.

In this investigation, the kernels were illuminated using diffuse fluorescent lighting. Fluorescent lighting was chosen
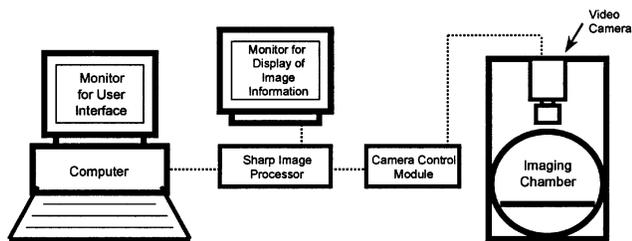
Figure 1. This diagram shows an image processing system.

Figure 2. The diffuse lighting chamber with fluorescent lighting.

due to (1) the availability of rare earth–activated phosphor lamps for enhanced color rendition and visual clarity, (2) long lamp life compared with incandescent (20,000 vs. 2,000 h), (3) cooler operating temperature due to higher operating efficiency, (4) less generation of infrared wavelengths that tend to bias video camera sensors, and (5) availability of physical lamp size and power level that matched dimensions of the lighting chamber.

Two Philips brand Ultralume U–tube lamps (FB40/30U/6 and FB40/35U/6) were combined to approximate the camera's factory calibrated light temperature. These specialty lamps were found to perform well in comparison with halogen and other types of lighting investigated. A high frequency (>20 kHz) ballast was used to eliminate lamp flicker inherent in a 60–Hz AC circuit.

Lamps were attached to the bottom of a 6–mm thick clear polycarbonate plastic imaging stage and placed inside a white polycarbonate light diffusion tube of 240–mm diameter, 760–mm length, and 2.4–mm wall thickness as shown in figure 2. Reflective opaque black paper placed on the bottom side of the imaging stage and over the lamps blocked direct light and provided good contrast for background segmentation of the corn kernel images.

An RGB color camera (Pulnix model TMC–74) was used to acquire corn kernel images. An adjustable zoom lens (12.5 to 75 mm) was fitted to the camera using a 25–mm extension tube. During image acquisition, the zoom lens was set at 75 mm. The camera lens was 10 cm from the imaging stage. The image frame processor captured 512– × 480–pixel images so that the resulting field of view was 15.8 × 14.7 mm. Spatial resolution was approximately 31 μm/pixel. The camera lens f–stop was set at F–16.

The image frame processor used a Windows–based dynamic link library (DLL) to provide the interface for control communications. A user interface, written in Visual Basic, made function calls to the DLL and executed selected image processing algorithms. Due to inherent noise in video camera signals, a color frame–averaging algorithm was developed for use with the frame processor. Red, green, and blue frames were captured sequentially and copied to summing buffers on the board. After 10 color frames were captured, the RGB sums were passed through a look–up table so that an averaged color image could be obtained. The color frame averaging algorithm was implemented in the frame processor hardware buffers. A detailed description of the procedure implemented is given in Steenhoek (1999).
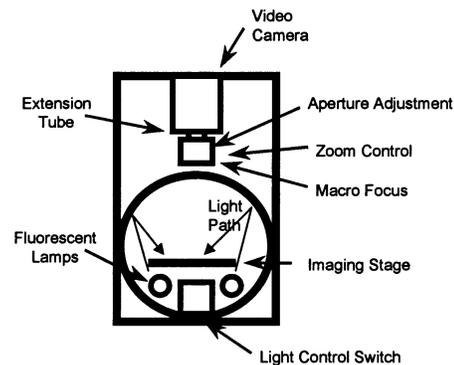
IMAGE ACQUISITION

Three replicate frame–averaged images for each of the 720 corn kernels were obtained using the image acquisition system. The camera and lighting system were switched on for 10 min prior to acquiring any images for electrical warm–up and stabilization. For each replication, kernels were presented to the camera in a random order. The camera was white balanced after every 10 kernel images were taken to compensate for any drift due to electronic heating.

IMAGE SEGMENTATION

Identification of features to segment, acquisition of training exemplars, and optimization of a probabilistic neural network architecture to segment the images are described in Steenhoek et al. (2001). Briefly, attributes representing features in sound, germ–damaged, and blue–eye mold–damaged corn kernel images were identified as RGB pixel regions: blue–eye mold damage, germ damage, sound germ, shadow in sound germ, hard starch, and soft starch. A sampling program was written to extract red, green, and blue pixel values from regions representing each of these color pattern features. The 14,427 image pixel RGB values collected were divided into a set of 778 exemplars for training of the probabilistic neural network weights, 737 exemplars for adjustment of the probabilistic neural network universal smoothing factor, and the remaining 12,912 exemplars were reserved for network validation. The probabilistic neural network implemented in Ward Systems NeuroWindows dynamic link library (Ward Systems Group, 1993) was optimized by selecting a universal smoothing factor that gave optimal network classification accuracy. Image segmentation using the trained networks was implemented on the frame processor board in hardware via values stored in a preprocessed look–up table. Red, green, and blue values from each corn kernel image pixel were mapped to appropriate gray levels for each of the color pattern categories. Pixels having red or green levels less than 32 were mapped to a gray level of 25 to represent background. Pixels having red, green, blue values corresponding to color pattern categories of blue–eye mold damage, germ damage, shadow in sound germ, sound germ, hard starch, and soft starch were mapped to gray levels of 100, 125, 150, 175, 200, and 250, respectively.

MEASUREMENT OF SEGMENTED FEATURES WITHIN IMAGES

The segmented images were then thresholded at each level (100, 125, 150, 175, 200, and 250) to create binary images with blobs representing different categories. Morphological filtering using erosion and dilation was performed prior to a labeling operation to remove small disconnected blobs and reduce the overall number of blobs by joining fragments. The frame processor board having 8–bit memory buffers had a maximum limit of 255 labels, making these operations a necessity before counting number of blobs for each segmented feature and number of pixels within each blob. Features for blue–eye mold, germ damage, and shadow in sound germ were eroded twice and then dilated twice before the labeling operation. Areas representing sound germ, hard starch, and soft starch were dilated twice and then eroded twice before the labeling operation was performed. The labeling operation allowed the blob pixels area and number of blobs related to each color pattern to be measured. Additional features were derived as detailed in table 2. In total, 12 features were used as network inputs.

APPLICATION OF NEURAL NETWORK
FOR IMAGE CLASSIFICATION

The probabilistic neural network (PNN) architecture implemented is illustrated in figure 3. The 12 input features were mapped to outputs representing kernel categories of sound, blue–eye mold, and germ damage. For each network output, a value between 0 and 1 represented the network's predicted probability for that category. A winner–take–all decision rule (largest output wins) gave the expected classification. Ward Systems Group (1997) NeuroShell
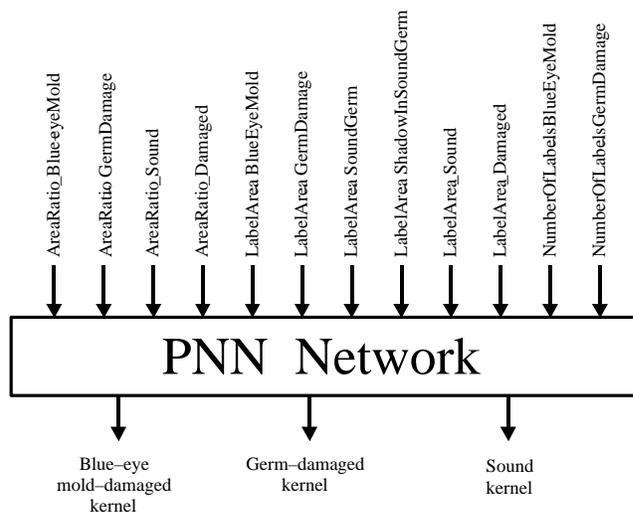

Figure 3. Kernel classification network architecture.

EasyClassifier software was used to implement a genetic variant of the PNN that applied an independent smoothing factor according to the relative importance of each input variable. The algorithm in NeuroShell EasyClassifier software required only a training and validation set. Of the 2,160 original corn kernel images, 252 (84 nonconcurrence kernels × 3 replicate images) were excluded from network modeling due to inspector nonconcurrence. Segmented features from 477 images were used to train the network. The remaining 1,431 images were used to validate the network.

RESULTS AND DISCUSSION
HUMAN INSPECTION OF CORN KERNELS

Inspection results summarized from Steenhoek (1999) are given in table 3. Of the 720 kernels inspected, 636 kernels received identical scores (concurrence scores) from each of the four inspectors. For the remaining 84 kernels, at least one inspector score differed. The fact that 84 kernels (12%) of 720 had different inspector opinions points out the large variability and subjectivity of the human grading process. Of the 84 kernels with different inspector scores, 51 (7%) kernels were due to differences in inspector opinion between blue–eye mold damage and germ damage categories. It is possible that these kernels may have contained both types of damage. Inasmuch as either category would have designated the kernel as damaged in the FGIS grading system, misclassification between damage categories should not be considered a serious error. Of greater concern was the finding that, in 5% of the evaluations (33 kernels out of 720), one or more inspectors disagreed on whether a kernel should be categorized as sound or damaged.

NETWORK PREDICTION OF KERNEL CLASSIFICATION

The NeuroShell Easy Classifier genetic PNN algorithm required 2.2 h on a 200–MHz Pentium computer to iterate through the 128 generations needed for network convergence. Table 4 shows contingencies of classification for the training and validation scenarios. Correct classification of

Table 2. Input features for the network for kernel classification.

Feature	Description
LabelArea_BlueEyeMold	Total area for pixels classified as blue–eye mold
LabelArea_GermDamage	Total area for pixels classified as germ damage
LabelArea_SoundGerm	Total area for pixels classified as sound germ
LabelArea_ShadowInSoundGerm	Total area for pixels classified as shadow in sound germ
NumberOfLabels_BlueEyeMold	Number of blobs for segmented areas representing blue–eye mold
NumberOfLabels_GermDamage	Number of blobs for segmented areas representing germ damage
LabelArea_Sound	LabelArea_SoundGerm + LabelArea_ShadowInSound Germ + LabelArea_HardStarch + LabelArea_SoftStarch
LabelArea_Damaged	LabelArea_BlueEyeMold + LabelArea_GermDamage
AreaRatio_BlueEyeMold	LabelArea_BlueEyeMold/ LabelArea_AllPoints
AreaRatio_GermDamage	LabelArea_GermDamage/ LabelArea_AllPoints
AreaRatio_Sound	LabelArea_Sound/LabelArea_ AllPoints
AreaRatio_Damaged	LabelArea_Damaged/LabelArea_ AllPoints

Table 3. FGIS inspector kernel classification statistics.

	Kernels	Percent
Majority (3 of 4) inspector classification sound	10	1
Majority (3 of 4) inspector classified damaged	18	3
Two inspectors classified sound, two damaged	5	1
Misclassifications between blue–eye mold and germ damage	51	7
Four inspector concurrence	636	88
Total	720	100

the images used for network training was 78% for blue–eye mold, 96% for germ damage, and 94% for sound kernels (table 4a). Correct classification of the images reserved for validation was 78, 94, and 93%, respectively (table 4b). The network performed best in identification of germ–damaged kernel images and was effective in identification of sound kernel images. Some germ–damaged kernel images were misclassified as blue–eye mold and vice versa; however, both of these categories are considered as damage in the FGIS grading system and their exact categorization is not an important issue in the overall grade assignment. The network was least sensitive in identification of blue–eye mold, as 67 (15%) of the 457 blue–eye mold–damaged kernel images in the validation set were classified as sound. By adding an additional decision layer to the network output that combined the similar categories of blue–eye mold and germ damage into one damage category, performance was enhanced. Table 4c shows that with an additional layer of decision on the network output, damaged and sound categories could be predicted with 92 and 93% accuracy, respectively.

Table 4a. Agreement matrix for network classification.[a]

	Actual Blue–Eye Mold	Actual Germ Damage	Actual Sound	Total
Classified blue–eye mold	116	6	10	132
Classified germ damage	8	149	1	158
Classified sound	25	0	162	187
Total	149	155	173	477
Percent correct	78	96	94	90

[a] Training dataset: blue–eye mold, germ damage, and sound classification.

Table 4b. Agreements matrix for network classification.[a]

	Actual Blue–Eye Mold	Actual Germ Damage	Actual Sound	Total
Classified blue–eye mold	356	24	33	413
Classified germ damage	34	429	3	466
Classified sound	67	4	481	552
Total	457	457	517	1431
Percent correct	78	94	93	89

[a] Validation dataset: blue–eye mold, germ damage, and sound classification.

Table 4c. Agreement matrix for network classification.[a]

	Actual Damaged	Actual Sound	Total
Classified damaged	843	36	879
Classified sound	71	481	552
Total	914	517	1431
Percent correct	92	93	93

[a] Validation dataset: sound and damaged classifications.

DISCUSSION

The image segmentation procedure (Steenhoek et al., 2001) proved effective in identifying color regions within the corn kernel images; however, some artifacts appeared in many of the segmented images. Some difficulties were encountered along the kernel boundaries where natural curvature of the kernel was sensed as darker areas and misclassified as damaged regions. For several of the blue–eye mold kernels, the blue–eye mold area was misclassified as shadow in sound germ, and for several sound kernels, the shadow in sound germ was misclassified as blue–eye mold. Blue–eye mold kernels were cut open, per FGIS procedure, after inspection and imaging to verify that they were not misidentified as kernels with purple plumule (a rarely occurring color marking).

The image acquisition process in which 10 frames were captured and averaged required about 1 second. For this study, kernels were hand placed, germ side up under a single camera due to the knowledge that almost all corn kernel damage occurs in the germ area. For complete automated corn kernel inspection, and a true comparison with the human inspector scenario, the vision system should view all sides of the kernel.

CONCLUSIONS

This study has shown that the basic concept of color patterns for use in image segmentation combined with neural networks for classification of segmented images holds promise. Major categories of corn kernel damage within the FGIS grading system were found to be blue–eye mold and germ damage. Seven hundred twenty kernels representing blue–eye mold, germ damage, and sound categories were obtained and evaluated by four inspectors on the FGIS Board of Appeals and Review. It was found that inspectors differed in opinion for 12% of the 720 kernels, with 5% of these different opinions being between sound and damaged categories. A computer vision system was developed to capture replicate color images of each of the 720 sample kernels. Images were segmented into blue–eye mold, germ damage, sound germ, shadow in sound germ, hard starch, and soft starch area categories using the procedure developed in Steenhoek et al. (2001). Morphological measurements extracted from each of the categories were used as inputs to a probabilistic neural network for prediction of the kernel image classifications of blue–eye mold–damage, germ damage, and sound categories. Correct classification on validation images was 78, 94, and 93% for blue–eye mold, germ damage, and sound kernels, respectively, with an overall classification accuracy of 89%. With an additional

layer of decision added to the network output, damaged and sound categories could be classified on validation images at a respective accuracy of 92 and 93%.

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