Estimation of *Fusarium* Scab in Wheat Using Machine Vision and a Neural Network[1]

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ABSTRACT

A neural network was used to relate color and texture features of wheat samples to damage caused by *Fusarium* scab infection. A total of 55 color and texture features were extracted from images captured by a machine vision system. Random errors were reduced by using average values of features from multiple images of individual samples. A four-layer backpropagation neural network was used. The percentage of visual scabby kernels (%VSK) estimated by the trained network followed the actual percentage with a correlation coefficient of 0.97; maximum and mean absolute errors were 5.14 and 1.93%, respectively. A comparison between the results by the machine vision-neural network technique and the human expert panel led to the conclusion that the machine vision-neural network technique produced more accurate determination of %VSK than the human expert panel.

The estimated yield losses caused by *Fusarium* head blight (scab) in Minnesota have been as high as 33%, with tremendous variations in damage from field to field. Buyers and inspectors must "pick" scabby wheat during grading to determine appropriate dockage on lots offered for sale. Because the disease is often accompanied by the production of toxic deoxynivalenol (DON), the level of DON measured by chromatography methods has been proposed for estimation of percentage of visual scabby kernels (%VSK) through statistical models. However, the low correlation coefficient between DON and VSK does not permit an accurate estimation of scab-infection rate. Chromatographic measurement of DON is expensive and time-consuming. The subjective approach utilizes the appearance, such as color and shape, of the wheat kernels. For example, the VSK have a chalky white color that is easily distinguished in the grain samples. However, this approach does not guarantee a consistent and reliable estimation due to the subjective nature of the method. Effort has been made to instrumentally measure the color features so that the VSK could be objectively identified. Currently, there is no reliable objective and fast inspection method available due to the difficulties in quantification of the color difference.

The objective of this research was to extract and quantify color-related features using machine vision and image processing techniques, and relate these features to %VSK through neural network computing techniques.

Machine vision techniques have been used to evaluate grain quality and classify grain varieties based on color and geometric features of grains (Gunasekaran and Paulsen 1986, Gunasekaran et al 1988, Neuman et al 1989, Zayas et al 1989, Shearer and Holms 1990). Color-related features that can be extracted from machine vision images include intensity, saturation, hue, and texture (Shearer and Holms 1990, Gonzalez and Woods 1992).

Because of the large number of features, and the many unknown relationships between these features and grain quality indicators, conventional statistical methods fail to provide a reliable tool for the estimation of grain quality indicators. Many researchers have used artificial neural networks to relate the color-related features to the grain quality for classification (Bleyberg et al 1991; Lao 1992; Burks et al 1994; Ruan et al 1995; Ng et al 1998) because artificial neural networks are capable of dealing with highly complex, nonlinear, and noisy problems (Marilyn and Illingworth 1990). Neural networks are computing techniques that simulate the human learning process (i.e., learn from examples). It resembles the brain in two respects: 1) knowledge is acquired by the network through a learning process; and 2) interneuron connection strengths, known as synaptic weights, are used to store the knowledge. Neural networks learn from or are trained with cases, to which the outputs or responses are known. The trained networks, when presented with new cases where the outputs are unknown, are then capable of producing outputs or answers to the cases. Neural networks are particularly suitable for problems where human insight, creativity, and judgment are normally required.

The present study emphasized the development of new methods for extraction of color-related features from the machine vision images of wheat kernels. The extracted features were used in the development of a neural network for estimation of %VSK.

MATERIALS AND METHODS

Wheat Samples

Hard red spring wheat samples (180) were collected as part of a grain-quality survey conducted by the Department of Plant Pathology at the University of Minnesota in 1993. For every sample, the number of normal (N_n) and scabbed kernels (N_s) was counted, and the "actual" VSK was calculated as:

$$\text{VSK} = \frac{N_s}{N_s + N_n} \times 100 \tag{1}$$

The VSK of the 180 samples fell into a range of 0–41%. The 180 samples were then divided into two portions: training samples (142) and testing, or prediction, samples (38). The training samples were further divided into 38 groups based on VSK value. Each group consisted of a number of samples with same VSK value. One 0% VSK sample was "made" by picking all scabby kernels out of the sample; it was added to the training samples to make a total of 39 groups for training. The 38 prediction samples represented VSK values of 1–41%. No 0% VSK sample was used for prediction.

All the samples had also been graded previously by a human expert panel. The panel was composed of three trained staff members in the Department of Plant Pathology at the University of Minnesota. The panel had a series of 20 photo plates of wheat kernels with known %VSK values ranging from 0 to 41%, to which each sample was visually compared and then given a best %VSK value, which will be referred to here as human expert panel determined %VSK.

Image Acquisition

The machine vision system used for image acquisition consisted of a TMC-7 color camera (Takenaka Ltd., Sunnyvale, CA) equipped

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with an AC10ZAME2 TV zoom lens (Asahi Precision Co. Ltd., Saitam-ken, Japan). The system was able to produce red, green, and blue digital signals. A light chamber with four FOS-9 Mini-Cool lamps (12V, 75W) (Cool-lux, Camarillo, CA) provided light source. A personal computer was used to operate the system.

To acquire an image of wheat kernels, ≈50 g of wheat kernels was evenly spread on a 168- × 126-mm black plate. The image of the kernels on the plate was captured with a resolution of 640 × 480 pixels at 8 bits/pixel for red, green, and blue components. All images were captured using the same optimized settings and stored for later analysis. Because this was a batch measurement instead of single kernel measurement, the images presented only rough estimates of visual characteristics of all the kernels shown on the images. Variations in orientation and occlusion will certainly result in differences in visual characteristics as observed from the images. To reduce random error caused by the orientation and occlusion of the kernels, the measurement must be repeated sufficiently to produce an average value that is close to the true visual characteristics of the kernels. To determine the optimal number of images for satisfactory error reduction, the central limit theorem was used. Central limit theorem is a statistical method that can be used to evaluate sampling distribution of mean. Given a population with a mean of μ and a standard deviation of σ, the sampling distribution of the mean has a mean of μ and a standard deviation of $\sigma/\sqrt{N}$, where N is the sample size for each mean. The standard deviation of the sampling distribution of the mean is called the standard error of the mean (σ_m). Note that the spread of the sampling distribution of the mean decreases as the sample size increases. In other words, σ_m decreases with increasing N. A small σ_m indicates high precision of the mean. The aim was to determine the minimal number of repeated images for a single sample that produce sufficiently low σ_m. In this study, a set of 112 images were obtained from a sample, each of which was taken after randomly distributing the kernels on the plate. From each of these images, four among the 21 color features extracted from the images were used to conduct the statistical analysis. The σ_m for each of these color features was calculated as:

$$\sigma_m = \frac{\sigma}{\sqrt{N}} \tag{2}$$

where N = 1, 2, 3, … 21. The σ_m was plotted against N as shown in Fig. 1. It was observed that σ_m decreased only slightly when N > 10, suggesting that ≈10 repeated images from a single sample would be sufficient to produce an average value with credible precision. In this study, 10–12 repeated images for each sample were used in neural network training and testing.

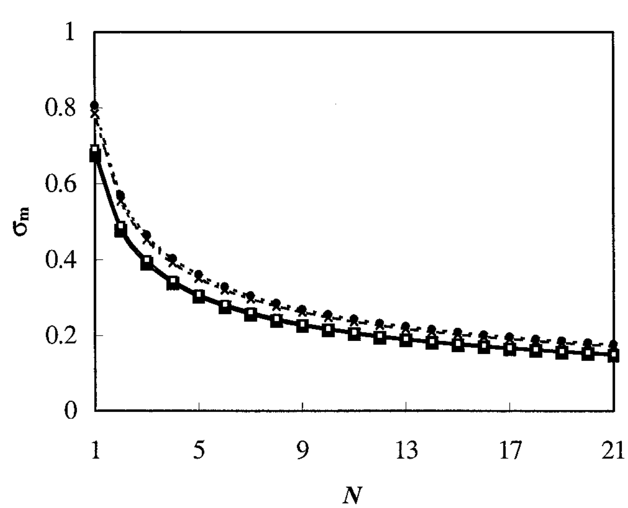

Fig. 1. Standard deviations of mean (σ_m) of four selected color features as a function of sample size (N).

Features Extraction

Three types of color-related features were extracted from the images of wheat kernels acquired using the machine vision system: color, texture, and color-indexing features. The total number of features used for neural network training and testing was 55.

Color features. A three-dimensional (red, green, and blue) color histogram of images captured from each wheat sample was determined by discretizing each color component (red, green, and blue) into 16 levels and counting the number of times each discrete color pixel in the image occurred in the 16 × 16 × 16 array, a total of 4,096 subspaces. The ratio of the value of a particular voxel (or the pixel number) to the total pixel number of the image was regarded as a color feature. After studying the three-dimensional histograms of images captured from three wheat samples with 10, 20, and 30% VSK, respectively, we observed that histograms of neighboring subspaces in a given region were similar in magnitude and changed in the same direction as VSK changed. Averaging the histograms in this region resulted in little loss of information. Following this logic, 21 such regions were identified, and the averaged histograms were used to represent individual regions. Therefore, the number of color features was reduced from 4,096 to 21.

Texture features. Among several approaches to texture analysis, the spatial gray-level dependent method (SGDM) is the most popular one. Color co-occurrence matrices (CCM) are the direct extension of SGDM and have proved to be very useful and accurate for identifying seven common cultivars of nursery stocks (Shearer and Holms 1990). For CCM, three color co-occurrence matrices can be obtained based on three color attributes: intensity, saturation, and hue, which can be expressed as: $Pi(i,j,d,\theta)$, $Ps(i,j,d,\theta)$, and $Ph(i,j,d,\theta)$, respectively. The co-occurrence matrices for intensity measures the probability that a pixel at one particular intensity will occur at a distinct distance (d), and orientation (θ) from any pixel, given that the pixel has a second particular intensity. In our study, the co-occurrence matrices were the sum of that with d = 1 and θ = 0, 45, 90, 135, 180, 225, 270, 315. Eleven texture features were calculated from every co-occurrence matrix expressed by $p(i,j)$ in the equations listed in Table I.

Applying this feature-extraction process to individual color parameters of intensity or $p_I(i,j)$, saturation or $p_S(i,j)$, and hue or $p_H(i,j)$, produced a total of 33 (11 × 3) texture features that were used to describe the image.

Color-indexing feature. Color indexing is a method based on color histogram matching (Swan and Ballard 1991). The study of color indexing by Swan and Ballard (1991) showed that color indexing is a powerful tool for identification of objects from a large number of different components, mostly because of its robustness to occlusion, as well as image and histogram resolution. This technique may be appropriate for this study because wheat kernels with similar VSK should have similar histograms, although their visual appearance may be different due to variations in orientation, patterns, and occlusion. Color indexing uses a histogram intersection technique to compare image and model (database) histograms. The histogram intersection technique states that for a pair of histograms, I (unknown image) and M (model), each containing n bins, the intersection of histograms is defined as:

$$\sum_{i=1}^{n} \min(I_i, M_{i)} \tag{3}$$

The result of the intersection of an M histogram with an I histogram is the number of pixels from the model that has corresponding pixels of the same color in the image. To obtain a fractional match value between 0 and 1, the interaction is normalized by the number of the pixels in the M histogram. The match value is then:

$$H(I,M) = \frac{\sum_{j=1}^{n} (I_j, M_j)}{\sum_{j=1}^{n} M_j} \tag{4}$$

$H(I, M)$ is higher if the number of pixels of a color in the image is closer to the number of pixels of that color in the model. After comparing the sample image to a database of stored models, a match value = maximum $H(I, M)$ is found so that the sample image is recognized by matching the sample image to the model image, from which the maximum $H(I, M)$ is produced.

In our study, the histograms of wheat samples with known VSK values were determined and indexed into the database of models. Then the histograms of unknown samples were determined and compared with those of the models. A match value was calculated

TABLE I
Equations for Calculating Texture Features

Texture Features	Equations[a]	Physical Meaning
Angular second moment	$f_1 = \sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1}[p(i,j)]^2$	Measure of homogeneity
Mean	$f_2 = \sum_{i=0}^{Ng-1} i p_x(i)$	Measure of image brightness
Variance	$f_3 = \sum_{i=0}^{Ng-1}(i - f_2)^2 p_x(i)$	Measure of variation of image intensity
Correlation	$f_4 = \dfrac{\sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1} ijp(i,j) - f_2{}^2}{f_3}$	Measure of intensity linear dependencies
Product moment	$f_5 = \sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1}(i - f_2)(j - f_2)p(i,j)$	Analogous to the covariance of the intensity
Inverse difference moment	$f_6 = \sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1}\dfrac{p(i,j)}{1+(i-j)^2}$	Contrast
Entropy	$f_7 = \sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1} p(i,j)\ln p(i,j)$	Measure of amount of order
Sum entropy	$f_8 = \sum_{k=0}^{2(Ng-1)} p_{x+y}(k)\ln p_{x+y}(k)$	No apparent physical interpretation
Difference entropy	$f_9 = \sum_{k=0}^{Ng-1} p_{x-y}(k)\ln p_{x-y}(k)$	No apparent physical interpretation
Measure of correlation	$f_{10} = \dfrac{f_7 - HXY1}{HX}$	No apparent physical interpretation
Measure of correlation	$f_{11} = [1 - e^{-2(HXY2 - f_7)}]^2$	No apparent physical interpretation

[a] $p_x(i) = \sum_{j=0}^{Ng-1} p(i,j)$, $p_{x+y}(k) = \sum_{i=0}^{Ng-1}\sum_{\substack{j=0\\k=i+j}}^{Ng-1} p(i,j)$, $p_{x-y}(k) = \sum_{i=0}^{Ng-1}\sum_{\substack{j=0\\k=i-j}} p(i,j)$, $HX = -\sum_{i=0}^{Ng-1} p_x(i)\ln p_x(i)$,

$HXY1 = -\sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1} p(i,j)\ln[p_x(i)p_x(j)]$, $HXY2 = -\sum_{i=0}^{Ng-1}\sum_{j=0}^{Ng-1} p_x(i)p_x(j)\ln[p_x(i)p_x(J)]$.

using the histogram intersection procedure as described above. If the match value for an unknown sample indicates that it matches a model histogram, then the VSK of the model sample is assigned to this unknown sample. The comparison between the actual and color-indexing estimated %VSK is shown in Fig. 2. The estimated result follows the actual one quite well. Therefore, the color-indexing estimated result was used as one of the input features to train the neural network.

Neural Networks

A four-layer backpropagation neural network architecture was used. The commercial neural network software NeuroShell2 (Ward Systems Group, Inc., Frederick, MD) was used for the network development and application. The key training parameters used were learning rate = 0.1, momentum = 0.1, and initial weight = 0.3. Training data sets (39) and prediction data sets (38), each of which consisted of 10–12 images for each sample, were used for training and prediction, respectively. In the training, 20% of the 39 training data sets were randomly set aside for test as part of the training process. The trained network was stored and used for later prediction. Upon completion of the prediction process, statistical data to indicate the performance of the trained network were read directly from the neural network program.

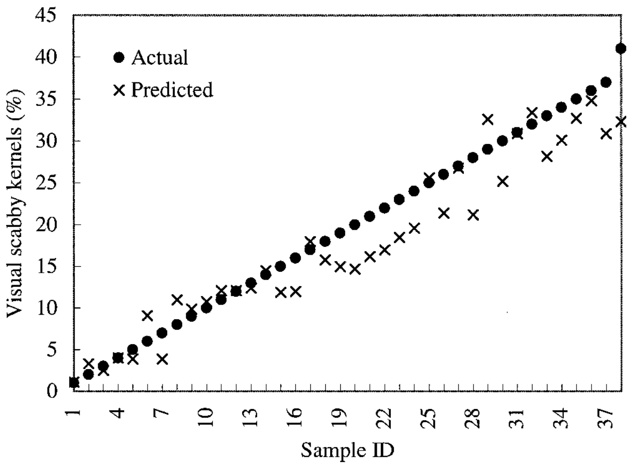

Fig. 2. Comparison between percentage of "actual" visual scabby kernels and percentage predicted by color indexing.

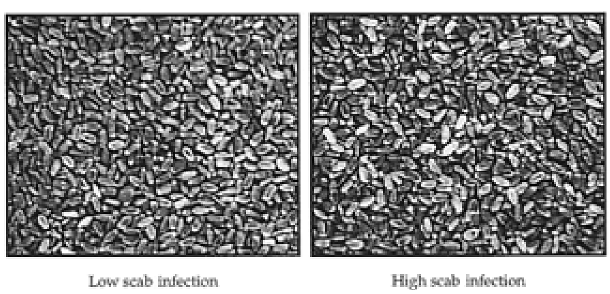

Fig. 3. Images of wheat samples with low and high scab infection (5 and 30% visual scabby kernels, respectively). Image on the left has less whiteness and contrast than the one on the right.

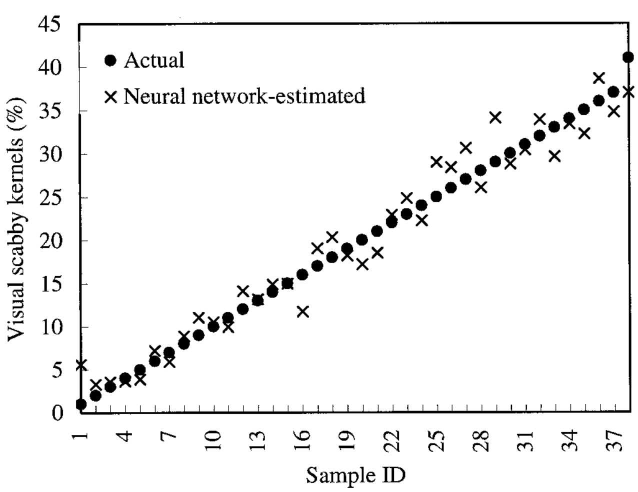

Fig. 4. Comparison between percentage of "actual" visual scabby kernels and percentage estimated by neural network technique.

RESULT AND DISCUSSION

Images of Wheat Samples

Figure 3 shows wheat sample images captured under the conditions mentioned earlier. The image on the left had less VSK (5%)

TABLE II
Evaluation of Neural Network Performance

R^2	0.95
Mean squared error	5.41
Mean absolute error	1.93
Maximum absolute error	5.14
Correlation coefficient	0.97
Percentage within 5%	18.42
Percentage within 5%–10%	34.21
Percentage within 10%–20%	31.58
Percentage within 20%–30%	10.53
Percentage over 30%	5.26

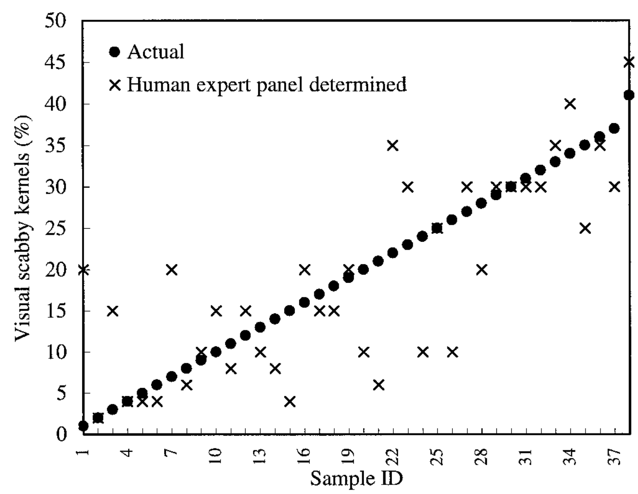

Fig. 5. Comparison between percentage of "actual" visual scabby kernels and percentage determined by a human expert panel.

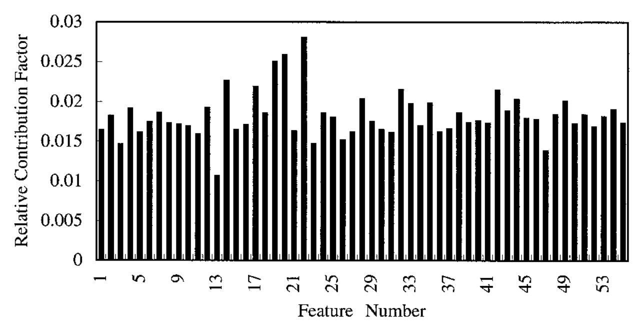

Fig. 6. Relative contribution of all features to the determination of percentage of visual scabby kernels. Numbers on x-axis represent the features used for training: 1–21 were color features, 22 was color indexing feature, 23–55 were texture features.

than the one on the right (30%). The difference in color characteristics between these two images is obvious to the naked eye. There are a greater number of lighter color kernels in the image with the higher degree of damage.

Estimation of %VSK Using the Neural Network

Figure 4 shows that the neural network-estimated %VSK follow the actual %VSK very well. To quantitatively determine the accuracy of the estimations, statistical analysis was performed. The result is shown in Table II. The correlation coefficient is 0.97. The maximum and mean absolute errors are 5.14% and 1.93%, respectively. On the other hand, Fig. 5 shows that the samples were poorly graded by the human expert panel. The comparison between the results shown in Figs. 4 and 5 led to the conclusion that the machine vision-neural network technique produced more accurate estimation of %VSK than did the human expert panel.

Features Contributing to Determination of %VSK

The contribution of the 55 input features (color, color indexing, and texture) to the determination of %VSK was evaluated using a routine built in the Neshell2 program. The weight of each feature was calculated as shown in Fig. 6. The color-indexing feature had the greatest weight in the neural network (feature 22 shown on the *x*-axis in Fig. 6), and therefore is most important to the estimation of %VSK. This can be attributed to the origin of the feature and its close relationship with infection rate. Figure 6 indicates, however, that none of the features shows a very small contribution to the estimation results, suggesting that the performance of the network may suffer if the number of input features is reduced.

CONCLUSION

In this study, a total of 55 color and texture features were extracted from images of wheat samples captured using a machine vision system. Among these 55 features, there were 21 color features obtained using a three-dimensional histogram method; 33 texture features calculated using the CCM method; and one color-index feature also based on the three-dimensional histogram method. To reduce the random errors due to kernel orientation, as well as variations in lighting and image digitizing, values of individual features used in neural network training and application were averages of 10–12 images of each wheat sample. The trained neural network produced excellent estimation of %VSK and is more accurate than the human expert panel. Further study would facilitate the development of a practical machine vision and neural network system for fast, accurate, and automatic determination of %VSK of wheat.

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