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Detection of sprouted wheat kernels using soft X-ray image analysis

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Abstract

Sprouted wheat kernels adversely affect bread and pasta making quality, thus lowering the grade and value to millers, bakers and grain dealers. In this study, the potential of using soft X-ray system in detecting the sprouted wheat kernels was evaluated. Sprouted kernels were produced by germinating seeds. Both the sprouted and healthy samples were X-rayed using a soft X-ray system. White specks were observed in all the sprouted kernel X-ray images. Algorithms were written to extract 55 image features including gray level modeling and histogram from the scanned images. Identification of sprouted and healthy kernels was determined using statistical and neural network classifiers. A four-layer back propagation neural network model correctly classified 90% and 95% of the sprouted and healthy kernels, respectively. Statistical classifier correctly identified 87% and 92% of the sprouted and healthy kernels, respectively.

Keywords: Sprouted kernels; Soft X-ray images; Statistical classifiers; Neural network classifiers

1. Introduction

Wheat is a commercial crop grown in over 120 countries worldwide and the world production accounts for 624.4 Mt (million tonnes) (FAO, 2006). An important quality trait linked to wheat export is sprouted kernels. When a large portion of kernels in a lot get sprouted, they are usually fed to animals, thus leading to economic loss. Damp harvest conditions and unfavorable weather cause the wheat kernels to sprout. Sprouting lowers test weight and flour yield, lowering the grade and value to the miller. Sprouted wheat kernels have adverse effects on bread quality because of the starch degrading enzyme α-amylase (Kruger, 1994).

Sprout damage leads to sticky dough which causes handling problems, coarse crumb structure and gummy crumb (Moot & Every, 1990). Excessive levels of α-amylase in the sprouted kernels impair the quality of the dough and the final baked product because of its effect in reducing the viscosity of the dough (Rasper & Walker, 2000). Sprouted wheat kernels affect the effective bread slicing (Dexter, 1993) and lower the number of loaves of bread obtained from a given mass of flour (Tkachuk, Dexter, & Tipples, 1991). In semolina and pasta processing, sprouted kernels increase semolina speck counts, reduce shelf life of dried pasta and increase cooking loss (Dexter, Matsuo, & Kruger, 1990; Matsuo, Dexter, & MacGregor, 1982).

The common methods of estimating sprouted wheat kernels are visual assessment by inspectors and falling number test. Visual estimation of sprout damage gives only a rough indication and it is inconsistent and subjective in nature. Falling number serves as a gauge for α-amylase activity, but it is time consuming and depends on the degree of ripening (Mares, 1993). Millers, bakers and other grain buyers rely on the index of falling number before purchasing the grain. The other methods of determining sprouted kernels are measurement of amylograph viscosity and chemical assays.

Electromagnetic waves with wavelengths ranging from 1 to 100 nm are called soft X-rays. The low penetration power and ability to reveal the internal density changes

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make soft X-rays suitable to be used for agricultural products. The soft X-ray method is rapid and takes only a few seconds (3–5 s) to produce an X-ray image. Wheat seeds irradiated with soft X-rays do not change their stored starch into sugar when exposed to short periods (Benedict & Kersten, 1934). Soft X-rays do not affect seed germination or cause chromosome damage (Kamra, 1976). With the advent of technology, the cost of X-ray systems is decreasing. Researchers have demonstrated the application of soft X-ray images in detecting infestations in wheat (Fornal et al., 2006; Karunakaran, Jayas, & White, 2003), determining mass flow rate of grain (Arslan, Inanc, Gray, & Colvin, 2000), classifying vitreousness in durum wheat (Neethirajan, Karunakaran, Symons, & Jayas, 2006), assessing viability of seeds, and inspecting packed fruits (Davies, 2000). Hence, the soft X-ray system can potentially be employed at grain terminal elevators for insect infestation detection and kernel hardness determination. Sprouted kernels are less dense than the healthy kernels (Tkachuk et al., 1991). The hypothesis of our study is that the difference in density between sprouted and healthy kernels can be used in detection and classification of the sprouted wheat kernels using the soft X-ray images.

The objectives of this study are:

(1) to determine the potential of soft X-ray images in classifying sprouted and healthy wheat kernels, and
(2) to determine the classification percentages of sprouted and healthy kernels from the soft X-ray images using statistical and neural network classifiers.

2. Materials and methods

2.1. Sample preparation

Canada western red spring wheat (variety *AC Barrie*), a widely grown wheat was selected for this study. A wheat sample of 3 kg was surface-sterilized by soaking in a 2% aqueous sodium hypochlorite solution for 15 min at 24 °C and rinsed with distilled water for about 20 min. The sample was soaked overnight for about 14 h in excess distilled water at 4 °C with one water change. The same sample was again rinsed well with distilled water and was spread on cellulose pads and germinated at 21 °C, 70% relative humidity. After 48 h, the samples were withdrawn and frozen at −30 °C and then freeze dried for about 96 h. Roots and coleoptiles were removed after freeze drying. The freeze dried samples were stored at −5 °C and were ready for scanning as sprouted sample. Another sample of 3 kg wheat was surface-sterilized and freeze dried immediately and used as healthy sample.

2.2. Falling number test

Falling numbers were determined for sprouted and healthy kernels using a falling number apparatus (Model 1500, Perten Instruments, Huddinge, Sweden). Standard AACC method 56-81B (AACC, 2000) was followed in determining the falling numbers. In the falling number apparatus, the falling number is determined by the time taken for a plunger to fall to the bottom of a precision bore glass tube filled with heated paste of wheat meal and water. The greater the sprout damage, the lower is the falling number. The falling numbers determined from the sprouted and healthy wheat samples were 62 and 272 s, respectively.

2.3. Image acquisition

A total of 2000 wheat kernels (1000 sprouted and 1000 healthy), selected randomly from each sample, were scanned using a soft X-ray imaging system. X-ray images of wheat kernels were acquired using a Lixi fluoroscope that has 62.5 μm resolution detection screen (Model: LX-85708, Lixi Inc., Downers Grove, IL). The X-ray tube voltage and tube current used were 13.5 kV and 185 μA. The wheat kernels were placed manually, crease down, on saran wrap (sample platform) and single kernels were X-rayed at a time. The scanned X-ray images of wheat kernels were digitized into 8-bit gray scale images at a resolution of 60 pixels/mm.

2.4. Feature extraction

Algorithms were developed in MATLAB (version 7.1, The Mathworks Inc., Natick, MA) to extract features from the X-ray images of sprouted and healthy wheat kernels. Thresholding procedure was used to remove the kernel from the background. A total of 55 image features were extracted and used for classification purpose. The normalized histograms were obtained for each kernel images and were grouped into 50 bins. The other features extracted were: kernel area ($\sum$ pixels), total gray value ($\sum$ gray values in kernel), mean gray value ($\sum$ gray values/$\sum$ pixels), inverted gray value (standard white to black mapping), and standard deviation of the gray levels.

2.5. Classification

The extracted 55 image features were reduced to 17 features using STEPDISC function (SAS, 2000). The Wilk's lambda (0.18) and the average-squared canonical correlation were used as the criteria of significance. The data set was then reduced to contain only 17 features. Linear discriminant parametric (PAR) classifiers were trained using the DISCRIM procedure (SAS, 2000). The discriminant analysis was used to determine the classification accuracy for the sprouted and healthy kernels. Classification accuracy is the percentage of kernels correctly identified as belonging to a specific class. Classification accuracies were determined by randomly selecting the training and testing sets three times. Three-fourth of the imaged sprouted and healthy kernels were used as training sets and the remain-

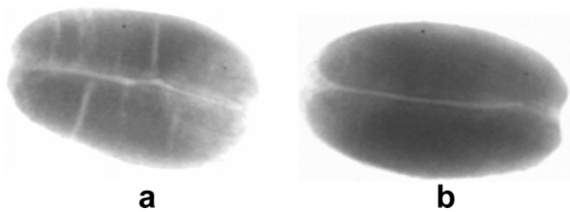

Fig. 1. X-ray images of (a) sprouted, (b) healthy wheat kernels (white speck indicates 'softened' endosperm in the sprouted kernel).

ing as the independent test sets. The average of the three trials was calculated as the mean classification accuracy.

A four-layer Back Propagation Neural Network (BPNN) suits best for grain classification applications (Jayas, Paliwal, & Visen, 2000). The classification accuracies were also determined using a four-layer BPNN. A neural network software package (Neuroshell 2, version 4.0, Ward Systems Group, Frederick, MD) was used for this purpose. The results of this classification were compared with the linear discriminant PAR classifier.

3. Results and discussion

Typical X-ray images of sprouted and healthy wheat kernels are shown in Fig. 1. The degradation of starch by α-amylase enzyme softens the kernel endosperm. This is reflected as white specks or internal fissures in the endosperm region of the sprouted kernel X-ray images but not in the healthy kernel X-ray images.

The mean total gray values were significantly less ($P < 0.05$) for sprouted wheat kernels than the healthy kernels. This may be due to the less absorption of photon energy in the sprouted kernels due to the breaking of starch by α-amylase.

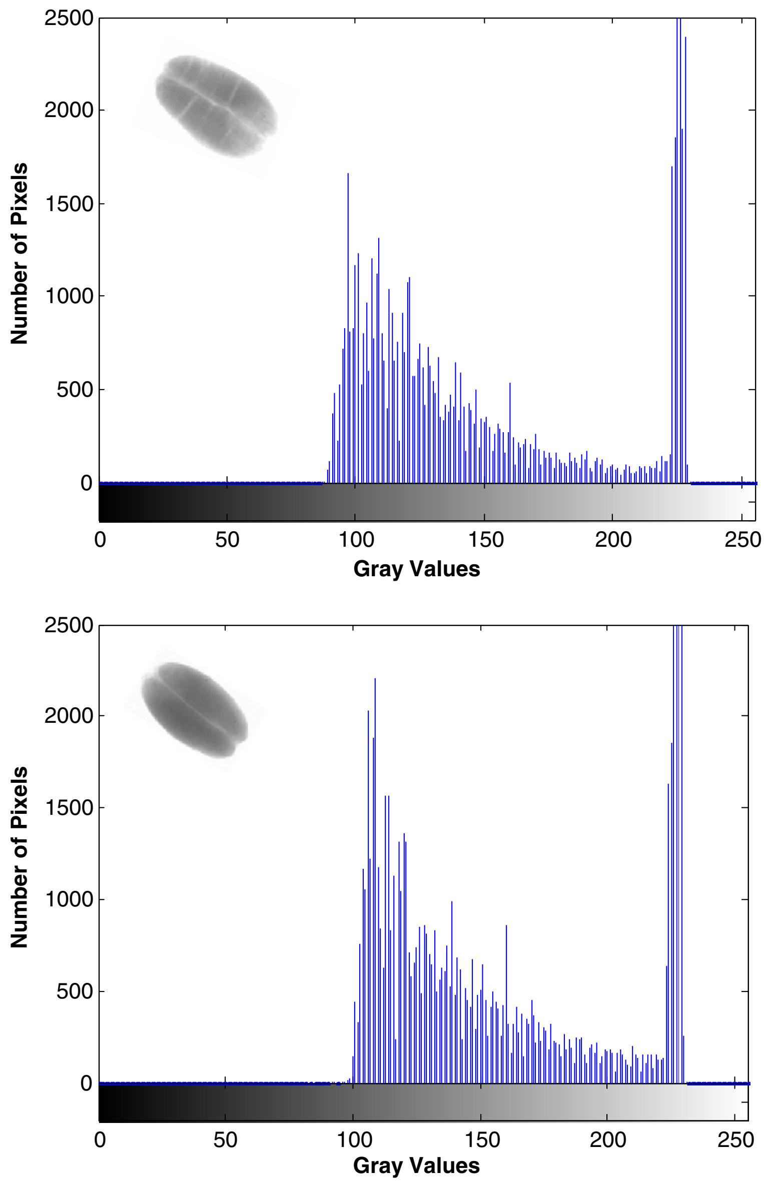

Fig. 2. Normalized histograms of sprouted (a) and healthy (b) wheat kernels.

Fig. 2 shows the gray level distribution from X-ray images of sprouted and healthy wheat kernels. Gray values in the histogram of sprouted kernel have numerically lower values between 100 and 150 gray values than healthy kernels. The brighter regions (white specks) in the sprouted wheat kernels cause this low number of lower gray values.

The mean histogram group values of 1000 sprouted and 1000 healthy wheat kernels are shown in Fig. 3. The histogram group values from 100 to 165 of healthy kernels were significantly higher than those of the sprouted kernels ($P < 0.05$). Since the endosperm is softened by the α-amylase enzyme, the X-rays passed through the sprouted kernels with less attenuation than the healthy kernels creating brighter regions with lower gray values in the sprouted kernel images. The 1000 kernel mass measured for sprouted and healthy kernels were 46.01 g and 48.67 g, respectively. Mean lower mass of sprouted kernels results in lower absorption of photon energy leading to lower gray values.

The histogram features were combined with the gray value features to determine the classification percentages of sprouted and healthy wheat kernels. Total gray value, total area, total inverted gray values were the most significant contributing features by the STEPDISC function (SAS, 2000). The classification accuracies determined using 17 features by the linear-function parametric statistical classifier and the four-layer BPNN of the sprouted and healthy kernels samples are shown in Fig. 4. Neural network classifier gives higher classification than the statistical classifier. A classification accuracy of 90% can be achieved for sprouted kernels using the four-layer BPNN model.

Linear discriminant classification is based on the relationship between categorical parameter and a set of interrelated parameters. In our study, we have two groups (1) sprouted kernel class and (2) healthy kernel class. Classification of a particular wheat kernel to find out which class it belongs is based on comparing the distance (Mahalanobis distance) of the particular kernel of unknown origin from the mean of the respective classes (McLachlan, 1992).

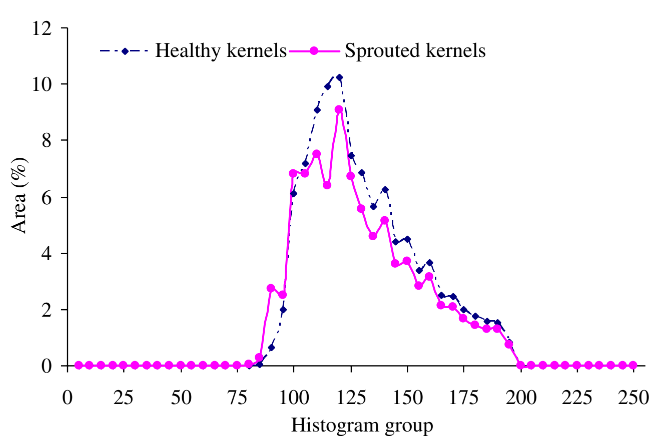

Fig. 3. Histogram groups of Canada western red spring sprouted and healthy wheat kernels.

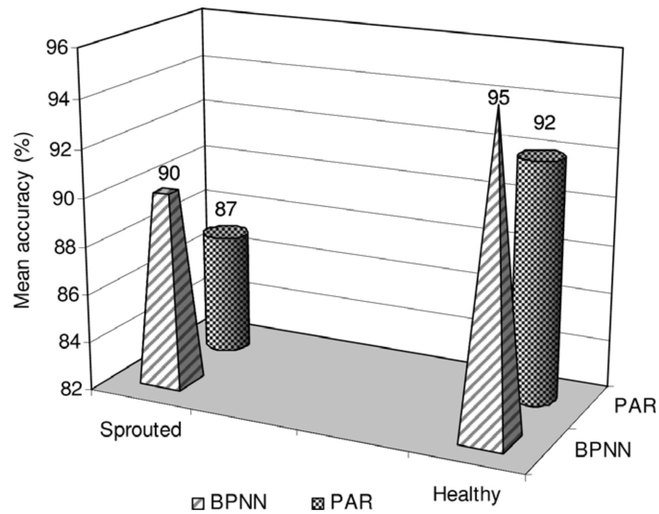

Fig. 4. Comparison of classification percentages of sprouted wheat kernels using statistical classifiers and BPNN. (Par: Parametric method; BPNN: Back propagation neural network method.)

In this study, the same selected features were used for both statistical and neural network classification. The goal of a NN classifier is to design a pattern classification system to find a model which best matches the training examples and generalizes well in the actual classification task. Four-layer multi layer perceptron is capable of forming an arbitrarily close approximation to any nonlinear mapping given sufficient neurons in the hidden layers (Zhang, Verma, & Kumar, 2004). The NN classifier was superior in classifying the kernels than the statistical classifier because of the neural network characteristics. Neural networks are able to learn from existing examples, making the classification adaptive and objective (Bishop, 1995; Kanellopoulos, Wilkinson, Roli, & Austin, 1997). Unlike statistical classifiers, NN classifiers do not make any assumption about distribution of data. Complex inter-correlation of features is best predicted by neural network classifiers by the learning epochs and hidden nodes. Neural network methods are more robust than statistical classifiers with respect to parameter tuning.

4. Conclusions

In this study, we have demonstrated the potential of soft X-ray images in detecting sprouted wheat kernels. Algorithms were written in MATLAB for feature extraction and quantification of gray values from the X-ray images. Statistical and artificial neural network classifiers were used for classifying the sprouted and healthy kernels. The BPNN classifier correctly classified 90% and 95% of sprouted and healthy kernels, respectively. The linear-function parametric classifier correctly identified 87% and 92% of sprouted and healthy kernels, respectively. The effect of orientation of kernels on classification during imaging needs to be addressed in future research. Further study using bulk samples in a line-scan X-ray imaging system is required before implementing the soft X-ray system for detecting sprouted kernels in the grain industry. Soft X-ray system can be used as an objective and rapid method, eliminating the subjective and time consuming classification of sprouted kernels by grain inspectors.

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