

Determination of Sprout-Damaged Barley Using Thermal Imaging

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ABSTRACT

Pre-harvest sprouting is a major problem associated with cereal grains which results in lowering of end use quality. Pre-harvest sprouting affects the malting quality of barley. The common methods to determine sprout damage are falling number, stirring number and amylograph peak viscosity, but these methods are time consuming. There are other methods such as near infrared hyperspectral imaging and soft-x ray analysis which are still in the research stage. Infrared thermal imaging technique to detect sprout damage is based on determining the changes in surface temperature distribution of grain which depends on the heat emission. An infrared thermal camera was used in this study to determine whether sprout-damaged barley could be detected from healthy barley. The results were analyzed using statistical and artificial neural network classifiers. The classification accuracies were 78.7, 78.9 and 88.5% for healthy; and 87.0, 87.5 and 87% for sprouted kernels, using linear discriminant analysis, quadratic discriminant analysis and artificial neural network, respectively. The results of the study show that thermal imaging has potential to determine sprout damage in barley.

Keywords: Grain, barley, sprout-damage, thermal imaging, classification, Canada.

1. INTRODUCTION

Sprouting of the seed is a natural occurrence in the life cycle of a plant. A sprouted kernel is defined as one in which the germ end has been opened by germination and exhibits a sprout, or in which the sprout has been broken off leaving only the socket (Huang and Varriano-Marston, 1980). Pre-harvest rain coupled with warm temperatures provides optimum condition for the kernels to germinate in the swath even before they are harvested from the field. Sprouting of cereal grain causes increased enzyme activity, loss of total dry matter, an increase in total protein, change in amino acid composition, and decrease in starch and increase in sugars (Lorenz, 1980). Pre-harvest sprouting causes harvest losses, reduced test weight, loss of seed viability and reduced flour quality resulting from protease and α -amylase enzyme activity

(Sorrells *et al.*, 1989; Moot and Every, 1990 cited from Martin *et al.*, 1998). Pre-harvest sprouting is mainly attributed to low seed dormancy before harvest (Rodríguez *et al.*, 2001).

Pre-harvest sprouting is a major issue in barley because when barley viability falls below 95%, malting barley is downgraded to feed grade with consequent financial loss (Bason *et al.*, 1993). Pre-harvest sprouted barley may lead to poor modified malt that is unsuitable for production of beer. Low extract yields, long runoff times, poor beer stability and off flavors are some problems that can result due to sprout-damaged barley (Heisel *et al.*, 2004).

Detection of sprouted barley is largely performed by visual inspection in Australia (Bason *et al.*, 1993). But this method is subjective, and lacks the sensitivity to detect mild damage that can significantly affect storage and further processing (Bason *et al.*, 1991). Visual estimation of sprouting in wheat is unreliable because much of the damage is done before germination of grain is visible (Jensen *et al.*, 1984 cited from Barnard *et al.*, 2005). In North America, the most widely used method for detecting pre-harvesting sprouting in barley at the malt house and elevator is the pearling of the sample and visual inspection (Heisel *et al.*, 2004). Schwarz *et al.* (2004) compared the pearling method with other techniques such as falling number (FN), stirring number (SN) and amylazyme method for assessment of pre-harvest sprouting in barley and they found that FN and SN methods were more sensitive than pearling method for identifying early stages of pre-harvest sprouting.

Falling number is widely used to determine sprout damage in wheat. Barnard *et al.* (2005) compared the falling number method with other methods such as stirring number, α -amylase, diastatic activity and WheatRite method. Their results showed that all methods evaluated showed significant correlation to each other but stirring number and falling number methods were most reliable for determination of pre-harvest sprouting. Koeltzow and Johnson (1993) compared the various sprout damage detection techniques such as falling number, stirring number (SN) and amylograph peak viscosity methods and concluded that the relationship between FN, SN and amylograph results are complex and it is difficult to convert results from one method to another. These methods are destructive and time consuming and cannot be used for online determination of sprout damaged kernels. Neethirajan *et al.* (2007) used X-rays to determine the incidence of sprouted wheat kernels. X-rays are difficult to use and pose a health hazard if the system becomes defective. Shashikumar *et al.* (1993) and Singh *et al.* (2009) demonstrated the potential of near-infrared hyperspectral imaging to classify sprouted and healthy kernels. But the drawback with hyperspectral imaging is the handling of enormous amounts of data and high cost associated with the imaging system (Sivakumar, 2006). Hence, there is a need to develop a simple, rapid, non-destructive and accurate method to determine sprout-damaged kernels.

Thermal imaging is a technique which converts the radiation emitted by an object into temperature data without establishing contact with the object. Infrared thermal imaging provides the surface temperature of an object and has wide application in fields such as medicine, electrical, mechanical and civil engineering. In agriculture, application of thermal imaging for evaluation of fruit maturity (Danno *et al.*, 1980), detection of bruises in fruits and vegetables (Danno *et al.*, 1977; Varith *et al.*, 2003), detection of foreign substance in food (Meinlschmidt and Margner, 2003), and detection of insect infestation in stored grain (Manickavasagan *et al.*, 2007) have been studied. It has been established that respiration and consequently the quantity of heat energy released per unit time would be higher in sprouted grain than in a healthy kernel

(Bailey and Gurjar, 1920; Proctor, 1994). In an earlier study (Vadivambal *et al.*, 2010), we demonstrated that thermal imaging has the efficiency of identifying pre-harvest spouting in wheat. Therefore, our hypothesis was that higher heat energy released by the sprout-damaged kernels can be used to differentiate sprouted kernels from healthy barley kernels using thermal imaging technique.

2. MATERIALS AND METHODS

2.1 Samples

The barley variety selected for the study was Certified Newdale. About 1 kg sample was surface sterilized by soaking in a 2% aqueous sodium hypochlorite solution for 15 min and then rinsed in distilled water. The sample was then soaked for about 16 h in distilled water. The water was drained and the grain spread on a cellulose pad and germinated at 21°C at 70% RH for 48 h. Then the samples were dried at room temperature to 12% moisture content and then kept in air-tight plastic bags until used for experiments. Healthy kernels were surface sterilized, rinsed and dried to 12% moisture content and kept in air-tight plastic bags using the similar procedures.

2.2 Image Acquisition and Feature extraction

An infrared thermal camera (Model: ThermaCAMTM SC500 of FLIR systems, Burlington, ON, Canada) with uncooled focal planar array type sensor was used to take thermal images of the sprout damaged and healthy barley kernels (Fig. 1). The camera captured images 240 × 320 pixels. Grain kernels at room temperature were placed on a heated plate (which was maintained at 30±1°C using a PID controller) in order to easily segment background from the area of interest and thermal images were captured by the camera. Technical specifications of the thermal camera, image acquisition and feature extraction techniques are described in detail in Vadivambal *et al.* (2010). Totally 2000 thermal images were acquired (one thousand healthy and one thousand sprout-damaged kernels), and Matlab (version 7.1, The Mathworks Inc., Natick, MA) was used for segmentation of grain kernel from background and temperature data extraction. Totally five temperature features (average, maximum, minimum temperatures of the grain kernel, range (temperature difference between maximum and minimum temperatures (Δt)), and standard deviation) were extracted from each thermal image using the developed Matlab algorithm.

2.3 Classification

The Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA) models were developed using PROC DISCRIM procedure in SAS (version 9.3, SAS Institute, Cary, NC, USA). Discriminant analysis classifies objects into one or more groups based on a set of features that define the object. Linear discriminant classifier uses pooled covariance in Bayes criteria to assign an unknown sample to one of the predefined groups. The quadratic discriminant classifier uses covariance of each class instead of pooling them in Bayes criteria for grouping of unknown samples (Naes *et al.*, 2002). Means of healthy and sprout damaged barley samples' temperature features were compared by Scheffe grouping method using SAS. Statistical classifiers were compared with a three layer back propagation neural network (BPNN) with default number of

neurons (44) in one hidden layer. Neural network software (Neuroshell 2, version 4.0, Ward Systems Group, Frederick, MD) was used for classification purposes. Five random data sets were created and the dataset was grouped as 60, 20, and 20% for training, testing and validation purposes.

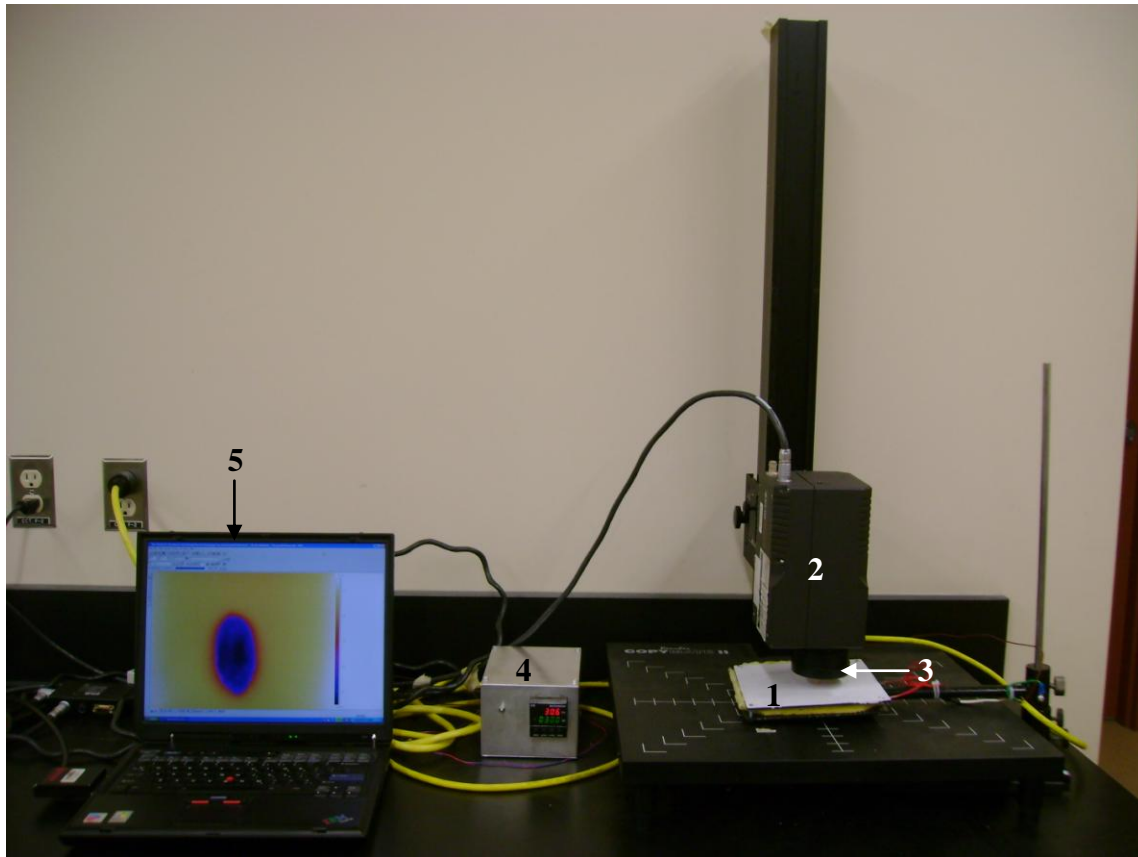


Figure 1. Experimental set-up for thermal imaging of healthy and sprout damaged barley kernels.
1. Heated Plate, 2. Thermal camera, 3. Close-up lens, 4. PID controller, 5. Data acquisition system

2.4 Falling Number Test

Falling number test is used to determine the sprout damage in barley using a falling number apparatus (Model 1500, Perten Instruments, Huddinge, Sweden) following the standard AACC Method 56-81B (AACC, 2000). A 7 g finely ground sample (particle size < 0.8 mm) of barley was mixed with 25 ml of distilled water in a test tube and shaken thoroughly forming slurry. A stirrer was placed in the tube and the test tube containing the slurry was placed in a hot water bath. The total time taken by the stirrer to reach the bottom is the falling number which reflects the sprout damage. The greater the sprout damage, the lower is the falling number.

3. RESULTS AND DISCUSSION

3.1 Temperature of the Healthy and Sprout-Damaged Barley Kernels

The average surface temperature of the thousand healthy barley kernels was 27.27°C whereas the average surface temperature of the sprout damaged kernels was 27.83°C. The thermal images of healthy and sprout damaged kernels are shown in Fig. 2. The average maximum and minimum

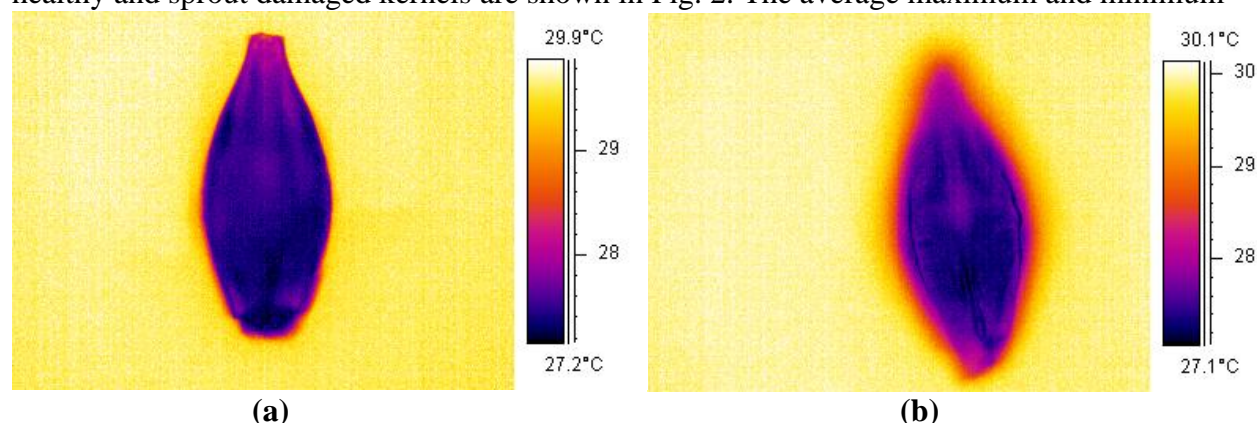


Figure 2. Thermal images of healthy (a) and sprout-damaged (b) barley kernels

surface temperature of healthy kernels were 28.29 and 26.69°C, respectively. The average maximum and minimum surface temperature of sprout-damaged kernels were 28.68 and 27.10°C, respectively. The temperature features other than range were significantly different ($P < 0.001$) for healthy and sprout-damaged kernels (Table 1). The classification of healthy and sprouted kernels using thermal imaging is based on the variation in the temperature of the kernels. The study conducted by Bailey and Gurjar (1920) has shown that the quantity of carbon dioxide respired and consequently the quantity of heat energy released per unit time is at a higher rate in sprouted wheat than in control wheat.

Table 1. Mean temperature values (\pm standard deviation) of healthy and sprout damaged kernels.

| Temperature values | Healthy kernels | Sprout damaged kernels |
|----------------------|----------------------------------|-------------------------------|
| Average temperature | 27.27 ^{a*} \pm 0.49** | 27.83 ^b \pm 0.52 |
| Maximum temperature | 28.29 ^a \pm 0.35 | 28.68 ^b \pm 0.36 |
| Minimum temperature | 26.69 ^a \pm 0.52 | 27.10 ^b \pm 0.55 |
| Range (Δt) | 1.60 ^a \pm 0.27 | 1.58 ^a \pm 0.30 |
| Standard deviation | 0.33 ^a \pm 0.09 | 0.40 ^b \pm 0.08b |

* Values with same letters in a row are not significantly different ($\alpha=0.05$) by Scheffe method

** Stanard deviation (n=1000)

3.2 Classification Using Statistical Analysis

The classification accuracy for healthy and sprout-damaged barley kernels using LDA was 78.7 and 87.0%, respectively. The classification accuracy for healthy and sprout-damaged barley kernels using QDA was 78.9 and 87.5%, respectively. The classification accuracy was higher for sprout-damaged kernels than the healthy kernels using both statistical classifiers. In our earlier study (Vadivambal *et al.*, 2010); the LDA and QDA classifiers developed from thermal images

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successfully identified 98.1 and 95.1% of pre-harvest sprouting in wheat kernels. Singh *et al.* (2009) studied the detection of sprout damaged wheat kernels using near infrared hyperspectral imaging and obtained a classification accuracy of 100% for healthy and sprouted wheat kernels.

3.3 Classification Using Artificial Neural Network

Five features (average temperature of the grain, maximum temperature of the grain, minimum temperature of the grain, range (Δt), and standard deviation) were used for artificial neural network classification. The mean classification accuracy of five trials for healthy and sprout damaged kernels were 88.5 and 87.0%, respectively. Table 2 shows the contributing factors and the contributing percentage of each factor. For both healthy and sprout damaged kernels, average temperature was the most important and the highest contributing factor. Compared to statistical classifier the classification accuracy was higher in ANN. Neethirajan *et al.* (2007) also reported higher classification accuracy using ANN than the statistical classifier for detection of sprout-damaged and healthy wheat kernels using soft X-ray image analysis. ANN classifier developed from thermal images yielded classification accuracies of 99.4 and 91.7% for healthy and pre-harvest sprout damage wheat samples (Vadivambal *et al.*, 2010).

Table 2. Contributing factor and contributing percent of each factor for ANN classification.

| Type of kernel | Contributing factor | Contributing percentage, % |
|----------------|----------------------|----------------------------|
| Healthy | Average temperature | 33.87 |
| | Range (Δt) | 18.93 |
| | Standard deviation | 17.59 |
| | Minimum temperature | 17.21 |
| | Maximum temperature | 12.39 |
| Sprout damaged | Average temperature | 33.20 |
| | Range (Δt) | 19.38 |
| | Standard deviation | 17.70 |
| | Minimum temperature | 17.32 |
| | Maximum temperature | 12.39 |

3.4 Falling Number Test

The results of the falling number test for five replications and average falling number for healthy and sprout-damaged kernels are given in Table 3. The average falling number values for healthy and sprout-damaged kernels were 235 and 62, respectively. Generally a falling number of 250 is considered as a cut-off for sprouting, but depending on the crop year this cut-off value varies between 220 and 250 (Buekert *et al.*, 2007). The results of falling number value clearly indicates a large degree of sprout damage in the samples.

Table 3. Mean \pm standard deviation of falling number values based on 5 replicates of barley

| Type of kernel | Falling number, s |
|----------------|-------------------|
| Healthy | 235 \pm 7.7 |
| Sprout damaged | 62 \pm 0 |

4. CONCLUSIONS

Thermal imaging was used to determine the sprout-damaged barley kernels from healthy kernels and statistical and neural network classifiers were used for classification purposes. The classification accuracies were: 78.7 and 87.0% for healthy and sprouted kernels, respectively, using LDA; 78.9 and 87.5% using QDA; and 88.5 and 87% using artificial neural network. The results of the study have shown that thermal imaging has a potential to identify single-sprout damaged kernels from the healthy kernels. Further studies are needed to determine sprout-damaged kernels in bulk samples using thermal imaging.

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