Determination of sprout-damaged barley using thermal imaging

R.Vadivambal[1], V. Chelladurai[1], D.S. Jayas[1], N.D.G. White[2]

(1. *Department of Biosystems Engineering, University of Manitoba, Winnipeg, MB, Canada, R3T 5V6*;

2. *Cereal Research Centre, Agriculture and Agri-Food Canada, Winnipeg, MB, Canada, R3T 2M9*)

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 to barley.

Keywords: grain, barley, sprout-damaged, 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

---

Corresponding author: D.S. Jayas, 207 Administration Building, University of Manitoba, Winnipeg, MB, Canada, R3T 2N2; Tel: (204) 474 9404, Fax: (204) 474 7568, Email: Digvir_Jayas@ umanitoba.ca

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-harvest 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 were complex and it was 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 medical, 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℃ 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: ThermaCAM^{TM} 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 (Figure 1).   The camera captured images of 240×320 pixels.   Grain kernels at room temperature were placed on a heated plate (which was maintained at 30±1℃ 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 of temperature difference between maximum and minimum temperatures (Δt)) and standard deviation) were extracted from each thermal image using the developed Matlab algorithm.
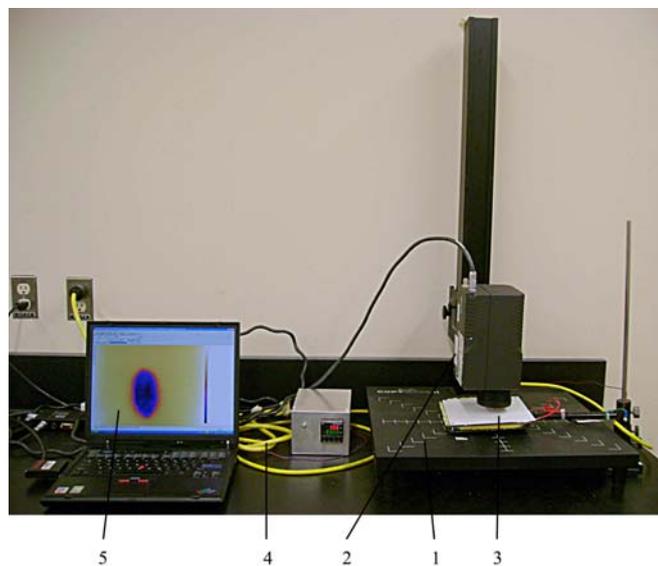
1. Heated Plate   2. Thermal camera   3. Close-up lens   4. PID controller
5. Data acquisition system

Figure 1   Experimental set-up for thermal imaging of healthy and sprout-damaged barley kernels

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.

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℃ whereas the average surface temperature of the sprout-damaged kernels was 27.83℃.   The thermal images of healthy and sprout-damaged kernels are shown in Figure 2.   The average maximum and minimum surface temperatures of

healthy kernels were 28.29℃ and 26.69℃, respectively. The average maximum and minimum surface temperatures of sprout-damaged kernels were 28.68℃ and 27.10℃, 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.
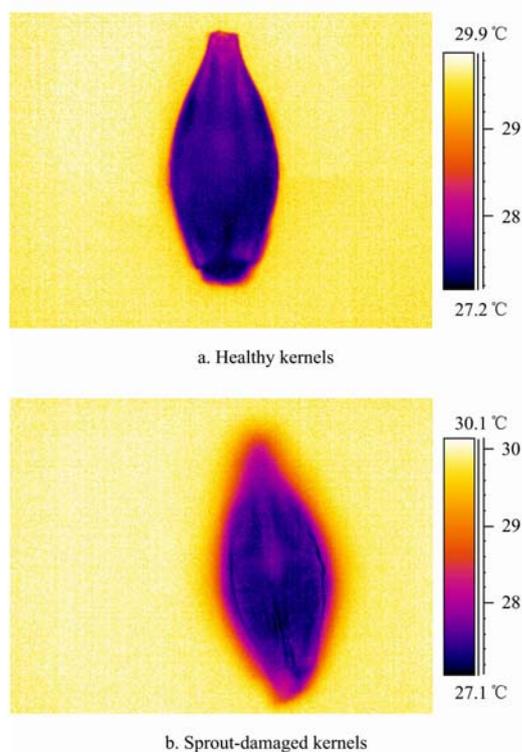

a. Healthy kernels

b. Sprout-damaged kernels

Figure 2   Thermal images of healthy and sprout-damaged barley kernels

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

Temperature values	Healthy kernels	Sprout-damaged kernels
Average temperature	27.27[a*] ± 0.49**	27.83[b] ± 0.52
Maximum temperature	28.29[a] ± 0.35	28.68[b] ± 0.36
Minimum temperature	26.69[a] ± 0.52	27.10[b] ± 0.55
Range (Δ*t*)	1.60[a] ± 0.27	1.58[a] ± 0.30
Standard deviation	0.33[a] ± 0.09	0.40[b] ± 0.08[b]

Note: * Values with same letters in a row are not significantly different (*α*=0.05) by Scheffe method;   ** Stanard deviation (*n*=1000).

表1中上标a、b表示什么？?

3.2   Classification using statistical analysis

The results of the statistical classifiers using LDA and QDA are given in Figure 3. 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 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.
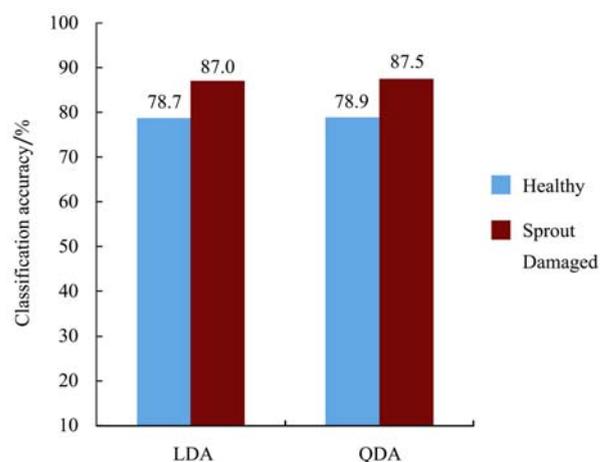

Figure 3   Classification accuracy for healthy and sprout-damaged barley kernels using LDA and QDA

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 (Δ*t*), and standard deviation) were used for artificial neural network classification. The mean classification accuracies 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-rays 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 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 (Bueckert et al., 2007). The results of falling number value clearly indicates a large degree of sprout damage in the samples.

Table 3　Mean ± standard deviation of falling number values based on 5 replicates of barley

Type of kernel	Falling number, s
Healthy	235* ± 7.7**
Sprout-damaged	62 ± 0

表中上标*、**表示什么？？

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.

Aknowledgements

References

AACC Method, 10 th Ed. 2000. Approved methods of the American Association of Cereal Chemists, Method 56-81B. St. Paul, Minn.: AACC.

Bailey, C. H. and A. M. Gurjar. 1920. Respiration of cereal plants and grains. II. Respiration of sprouted wheat. *The Journal of Biological Chemistry*, 44(1): 5–7.

Barnard, A., C. S. van Deventer and H. Maartens. 2005. Comparison between methods for estimating sprout damage in wheat. *South African Journal of Plant and Soil*, 22(1): 44–48.

Bason M. L., J. A. Ronalds and C. W. Wrigley. 1991. Screening for pregermination of barley at harvest. In *Proceedings of the 40th Australian cereal chemistry conference*, 120–125. Westcott T, Williams Y (eds). Melbourne, Australia: Royal Australian Chemistry Institute.

Bason, M. L., J. A. Ronalds, C. W. Wrigley and L. J. Hubbard. 1993. Testing for sprout damage in malting barley using the rapid visco-analyser. *American Association of Cereal Chemists*, 70(3): 269–272.

Bueckert, R. A., E. B. Lefol and B. L. Harvey. 2007. Early detection of non-visible sprouting in barley seed using rapid viscosity analysis. *Canadian Journal of Plant Science*, 87(1): 3–12.

Danno, A., M. Miyazato and E. Ishiguro. 1977. Quality evaluation of agricultural products by infrared imaging method: Grading of fruits for bruise and other surface defects. *Memoirs of Faculty of Agriculture, Kagoshima University*, 14: 123–138.

Danno, A., M. Miyazato and E. Ishiguro. 1980. Quality evaluation of agricultural products by infrared imaging method: Maturity evaluation of fruits and vegetables. *Memoirs of Faculty of Agriculture, Kagoshima University*, 16: 157–164.

Heisel, S., P. Schwarz and J. Barr. 2004. Preharvest sprout damage as measured by pearling. *American Society of Brewing Chemists*, 62(2): 59–62.

Huang, G. and E. Varriano-Marston. 1980. α-amylase activity and preharvest sprouting damage in Kansas hard white wheat. *Journal of Agriculture and Food Chemistry*, 28(3): 509–512.

Jensen, S. A., L. Munck and J. E. Kruger. 1984. A rapid fluorescence method for assessment of preharvest sprouting of cereal grains. *Journal of Cereal Science*, 2: 187–201.

Koeltzow, D. E. and A. C. Johnson. 1993. Comparison of sprout damage analysis techniques. In *Pre-harvest Sprouting in Cereals,* 391-399. M. K. Walker-Simmons and J. L. Ried (eds.). Minnesota: American Association of Cereal Chemists.

Lorenz, K. 1980. Cereal sprouts- composition, nutritive value, food applications. *Critical Review of Food Science and Nutrition*, 13(4): 353–385.

Manickavasagan, A., D. S. Jayas and N. D. G. White. 2007. Thermal imaging to detect infestation by *Cryptolestes ferrugineus* inside wheat kernels. *Journal of Stored Products Research*, 44(2): 186–192.

Martin, C., T. J. Herrman, T. Loughin and S. Oentong. 1998. Micropycnometer measurement of single-kernel density of healthy, sprouted and scab-damaged wheats. *Cereal Chemistry*, 75(2): 177–180.

Meinlschmidt, P. and V. Margner. 2003. Thermographic techniques and adopted algorithms for automatic detection of foreign bodies in food. In *Proceedings of Thermosense XXV*, 168–177. Bellingham, Wash.: The International Society for Optical Engineering.

Moot, J. D. and D. Every. 1990. A comparison of bread baking, falling number, alpha amylase assay and visual method for the assessment of pre-harvest sprouting in wheat. *Journal of Cereal Science*, 11: 225–234.

Naes, T., T. Isaksson, T. Fearn and T. Davies. 2002. A user friendly guide to multivariate calibration and classification, Chichester, West Sussex: NIR Publications.

Neethirajan, S., D. S. Jayas and N. D. G. White. 2007. Detection of sprouted wheat kernels using soft X-ray image analysis. *Journal of Food Engineering*, 81(3): 509–513.

Proctor, D. L. 1994. Quality and Grading of Grain. In Grain Storage Techniques- Evolution and Trends in Developing Countries. Food and Agricultural Organization Agricultural Services Bulletin No.: 109.

Rodríguez, M. V., M. Margineda, J. F. Gonzalez-Martin, P. Insausti and R. L. Benech-Arnold. 2001. Predicting preharvest sprouting susceptibility in barley: A model based on temperature during grain filling. *Agronomy Journal* 93: 1071–1079.

Schwarz, P., C. Henson, R. Horsley and H. McNamara. 2004. Preharvest sprouting in the 2002 midwestern barley crop: occurrence and assessment of methodology. *Journal of the American Society of Brewing Chemists*, 62(4): 147–154.

Shashikumar, K., J. L. Hazelton, G. H. Ryu and C. E. Walker. 1993. Predicting sprout damage by near-infrared reflectance analysis. *Cereal Foods World*, 38(5): 364–366.

Singh, C. B., D. S. Jayas, J. Paliwal and N. D. G. White. 2009 Detection of sprout and midge-damaged wheat kernels using near-infrared hyperspectral imaging. *Cereal Chemistry*, 86(3): 256–260.

Sivakumar, S. S. 2006. Potential applications of hyperspectral imaging for the determination of total soluble solids, water content and firmness in mango. M.Sc Thesis. McGill University, Montreal, Quebec, Canada.

Sorrells, M. E., A. H. Paterson and P. L. Finney. 1989. Milling and baking quality of soft white wheat genotypes subjected to preharvest sprouting. *Cereal Chemistry*, 66(5): 407–410.

Vadivambal, R., V. Chelladurai, D. S. Jayas and N. D. G White. 2010. Detection of sprout damaged wheat using thermal imaging. *Applied Engineering in Agriculture*, 26(6): 999–1004.

Varith, J., G. M. Hyde, A. L. Baritelle, J. K. Fellman and T. Sattabongkot. 2003. Non-contact bruise detection in apples by thermal imaging. *Innovative Food Science and Emerging Technologies*, 4(2): 211–218.