



A two-camera machine vision in predicting alpha-amylase activity in wheat



B.L. Shrestha, Y.M. Kang, O.D. Baik*

Department of Chemical and Biological Engineering, College of Engineering, University of Saskatchewan, Saskatoon, SK, Canada

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ABSTRACT

Sprout damage in wheat is a serious problem worldwide because damaged wheat kernels contain alpha-amylase, an enzyme that causes poor baking quality of wheat. A two-camera machine vision (MV) with a neural network was implemented to quantify alpha-amylase activity in wheat using 16 visual properties of the kernels. Kernels were separated at image level using the marker-controlled segmentation algorithm before the properties (color, texture, and shape and size) of dorsal and ventral sides of kernels were extracted. Alpha-amylase activity in wheat was assessed analytically. The neural networks were trained, validated, and tested using the visual properties as the inputs and alpha-amylase activity as the output. The trained neural network predicted alpha-amylase activity with an accuracy of 6913 U/L (rmse) and R^2 value of 0.72 for the wheat samples with alpha-amylase activity ranging over 178 to 28935 (U/L). Differences between visual properties of wheat samples calculated from the top and the bottom images was less than 0.5%. Light stability in time and influence of temperature on the cameras' color stability were less than 2% of the mean values. The challenges associated with the system, and recommendations to improve the system accuracy and robustness, and to decrease the system cost are presented.

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1. Introduction

Alpha-amylase is a key enzyme found in the sprout-damaged wheat. Quantification of this enzyme helps segregating wheat with varying degrees of sprout damage. Sprout-damaged wheat possesses poor baking qualities. Since wheat is one of the most important cereal grains of the world with a global production of 710 million metric tons (2013/2014), the sprout damage in wheat is an important problem worldwide (Statista, 2015).

Hagberg falling number (HFN) is currently used to quantify sprout damage in wheat. It is measured with the Hagberg test method (Perten, 1964), which is based on the kernels' alpha-amylase activities. Good quality wheat has a low alpha-amylase activity and a high HFN. For example, a HFN of 350 s or higher indicates low enzyme activity and sound wheat quality. This test provides an objective measurement of wheat quality, but the test is more suitable for laboratory use than on-site use at primary, transfer, or terminal elevators because it requires many steps in sample preparation, for example, grinding, moisture adjustment, weighing, etc. and these steps require expertise. This test method is

destructive and each test takes about 10 min to complete. Distilled water and calibration oil are required reagents.

Researchers have studied the correlation between whole grain area or endosperm cavity area and alpha-amylase activity in wheat kernels. Kindred et al. (2005) reported that the area of wheat kernel was not sufficient to determine the late maturity endosperm alpha-amylase activity. Evers et al. (1995) concluded that it was difficult to correlate kernel size to the enzyme activities in grains based upon a handful of experiment, and they suggested that a robust experimental base was important from which the deductions could be made. Farrell and Kettlewell (2008) demonstrated that the premature alpha-amylase activity was related with the increase in the grain area in some cases, but they concluded that there was no evidence of a mechanistic link between high alpha-amylase activity and the area. Use of only grain size and/or the endosperm cavity area to measure alpha-amylase activity seemed to be farfetched.

There is a serious drawback using a machine vision comprising of a single camera or a flatbed scanner. The system can easily miss part of a germ or even a whole germ unless the seeds are placed and spread manually on the sample tray. The impurities in the sample can also block some seeds from view. Each seed in the sample must be overturned to capture the image of the other side of the seed. This process is not only tedious, but it also creates a problem in maintaining identical kernels' IDs because the IDs are sensitive to

* Corresponding author.

E-mail address: oon-doo.baik@usask.ca (O.D. Baik).

Nomenclature

Symbols/abbreviations and Meaning

ANN	Artificial neural network
B	Blue
cbr	Closing by reconstruction
CC	Connected component
CWRS	Canadian western red spring
DCOM	Distributed component object module
FN	Falling number
FOV	Field of view
F _{top}	Measured feature value using the top camera
F _{bot}	Measured feature value using the bottom camera
G	Green

GUI	Graphical user interface
ID	Identification
imbot	Image produced from the bottom camera
imtop	Image produced from the top camera
Lum	Luminance
MC	Moisture content
MV	Two-camera machine vision
obr	Opening by reconstruction
R	Red
SEVSPTD	Severe sprout-damaged
SND	Sound
SPTD	Sprout-damaged
std	Standard deviation
U/L	Units per liter

the relative position of the kernels to the left edge of the whole image. Szczypinski et al. (2015) placed the seeds manually in a flatbed scanner to identify barley varieties. They reported that the identification accuracy could be improved significantly by using both sides of the seeds.

Because the various objective methods summarized above have had only limited success, visual inspection by a grain inspector has been the practice for a long time and continue to be used until a reliable objective method is developed. However, visual inspection has serious drawbacks of its own, that is, this method is purely subjective in nature, and therefore, a better approach is needed.

This work presents a machine vision that uses two cameras to “look” at both dorsal and ventral sides of kernels simultaneously. Since the area of wheat or germ area was not sufficient to predict the alpha-amylase activity in the wheat, this vision system was designed to extract 16 visual properties including color, texture, and shape and size of sound, sprout-damaged (SPTD) and severely sprout-damaged (SEVSPTD) wheat kernels. These features and analytically measured alpha-amylase activity (U/L) were then used to model a neural network for the objective quantification of the enzyme in wheat. Therefore this technique was an integration of “visual inspection” and objective method in quantifying the alpha-amylase activity in wheat.

It is critical to segment fused kernels in a digital image before extracting the visual properties of individual seeds. Many researchers have developed and/or tested segmentation algorithms to segment fused kernels in digital images (Paliwal and Wang, 2006; Kiratiratanapruk and Sinthupinyo, 2011; Hua et al., 2007; Hobson et al., 2009; Visen et al., 2001; Faessel and Courtois, 2009; Yan et al., 2011). These algorithms disjoined fused kernels with accuracies ranging over 55.4–100% depending upon the shapes and sizes of the grains, the number of grains in a cluster, and the way the grains formed the clusters. In summary, the success of segmentation algorithms appeared to be depended largely on the particular target objects and the background.

Watershed transformation algorithm always produces closed contours for the segmented objects, and is computationally feasible (Beucher and Lantuejoul, 1979) but the technique usually suffers with oversegmentation because it identifies the objects using the minimum gray values, and numerous minima are usually present in images due to the nature of the images and noises. Meyer and Beucher (1990) developed a marker-controlled segmentation method based on the internal (for the objects) and the external (for the background) markers. Later, Meyer (1994) extended their 1990's work to make it suitable for implementing in hardware. This latest work of Meyer was tailored to use in this research.

The objective of this study was to test a two-camera machine vision (MV) and a neural network for an objective quantification of alpha-amylase activity in wheat kernels for speed, accuracy, and portability. It will especially be suitable in primary and terminal elevators where space for specialized laboratory equipment is limited, and the ability to segregate deliveries with rapid turnaround is critical.

2. Materials and methods

2.1. Sprout-damaged wheat

Our industrial partner, Viterra Inc., Regina, Canada had provided us with a 40 kg of #1 Canadian Western Red Spring (CWRS) wheat for the project because this variety of wheat was common in western Canadian wheat deliveries. The initial moisture content (MC) of the wheat was $15.2 \pm 0.4\%$ wet basis (% w. b.). All MCs mentioned in this paper are based on %, w. b. unless otherwise stated, and were determined following ASABE Standards (ASABE R2008).

A total of 600 wheat kernels were considered. Twenty-five of sound kernels were hand-picked from the wheat lot at initial MC, and placed on a Whatman filter no. 2 fitted in a 9 cm-diameter petri dish and saturated with 2 ml of distilled water. The petri dish was put in a sealed plastic bag to prevent desiccation of the filter paper during the incubation period. The kernels were incubated in a temperature-humidity chamber (SH-641, Espec Corp., Osaka, Japan) set at 15 °C and 65% RH. A number of samples were prepared following the same procedure. The alpha-amylase activities of the wheat kernels that were incubated (germinated) for 3 d had a sharp transition, and fell between the alpha-amylase activities of the kernels incubated for 0–2 d (low), and 4–7 d (high). Therefore, the kernels that were incubated in 0–2, 3, and 4–7 d were assigned to sound (SND), SPTD and SEVSPTD classes respectively. The wet germinated kernels were dried at 22 °C to their initial weight (0.79 ± 0.05 g, triplicate) to ensure that the sprout-damaged kernels were back to the initial MC safe for storage (15.2%). The samples thus prepared were then stored in the sealed plastic bags at 4 °C.

2.2. Machine vision

Fig. 1 is the block diagram of the MV developed in this work. It consisted of two color smart cameras (RL04C-OC, 7 Watts, Ximea GmbH, Hansestraße 81, 48165 Münster, Germany) each embedded with a processor (Intel Atom Z510 1.1 GHz), a sensor (WVGA, active

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