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Research Paper

Detection of sprout damage in wheat kernels using NIR hyperspectral imaging

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The use of near-infrared (NIR) hyperspectral imaging (HSI) for detecting sprout damage in wheat kernels was investigated. Experiments were carried out to determine which spectral bands had the best potential for discriminating between sound and sprouted kernels. Two wavelengths were selected and combined into an index that was used to indicate the presence or absence of sprouting. Experiments with three wheat cultivars revealed that the proposed method is effective in identifying kernels for which the germination process has initiated, achieving 100% accuracy for the samples used in this study. It was also observed an imperfect correlation with the Falling Number (grain quality), making it challenging to accurately determine the degree of germination, especially if sprouts are not yet clearly visible. These results confirm the usefulness of the near-infrared spectral range for detecting chemical alterations in wheat kernels, as well as the fact that most information is usually contained in a few specific bands within such range.

1. Introduction

Sprouting occurs as a result of germination of wheat kernels following rainfall after maturity, reducing grain quality and value (Biddulph, Plummer, Setter, & Mares, 2008). The chemical properties of the sprouted grain can be significantly changed, causing important alterations on the concentrations of starch, sugar, proteins and dry matter (Lorenz & Valvano, 1981). In particular, the α-amylase enzyme is found in high concentrations in sprouted kernels, which affects baking quality and the premium paid for wheat (Singh, Jayas, Paliwal, & White, 2009). The grinding process is also heavily influenced by sprouting, both in terms of grinding energy requirements and distribution of the particle size (Dziki & Laskowski, 2010).

Sprouted kernels are also more vulnerable to diseases and insect infestations (Singh et al., 2009). Thus, it is very important to accurately measure the damage caused by sprouting so producers are paid fairly and the grains receive a proper destination.

In many cases, grain quality assessment and sprouting detection are performed visually. This visual selection, being a subjective task, is prone to psychological and cognitive phenomena that may lead to bias and optical illusions (Barbedo, 2016). Additionally, some cultivars have visual

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Nomenclature

FN	Falling number
FPA	Focal plane array
HSI	Hyperspectral imaging
NIR	Near-infrared
PCA	Principal component analysis
ROI	Pegion of interest
SI	Sprouting index
SWIR	Short-wave infrared
WRD	Water reflectance difference

characteristics that can lead to misclassifications (Singh et al., 2009). Delwiche, Yang, and Graybosch (2013) used computer vision (black and white images) and machine learning to explore the same visual cues used by human observer while removing the subjectivity of visual inspections. The authors tested several types of damage together, so they did not report how their system performed in the specific case of sprout damage. Another method exploring visual cues was proposed by Ebrahimi, Mollazade, and Babaei (2014), who employed RGB images for detecting several types of damage. Although the results reported for germinated kernels were good, sprouts had to be clearly visible for the system to work properly, preventing early detection.

Another widely employed method to estimate the grain quality loss associated to sprouting is the “Falling Number”, which is a measure closely related to the concentration of the α-amylase enzyme in the grains. This number indicates the suitability of the grains for milling (Biddulph et al., 2008): the higher the Falling Number (measured in seconds), the higher is the quality of the grain and, hence, the higher the payment grade. In Brazil, there are four classes defined by the Falling Number: enhancer (FN > 250 s), bread (FN > 220 s), domestic (FN > 220 s) and basic (FN > 200 s) (MAPA, 2010). Despite its advantages, the Falling Number method is destructive and relatively time consuming, making it unsuitable for online inspection (Singh et al., 2009). Additionally, low Falling Numbers are possible in the absence of sprouting, which may lead to misdetection (Mares & Mrva, 2008). Other common methods for detecting sprouted kernels include the measurement of amylograph viscosity and chemical assays (Neethirajan, Jayas, & White, 2007).

One way to overcome some of the limitations of the established approaches is to explore spectral differences between sound and sprouted kernels. Shashikumar, Hazelton, Ryu, and Walker (1993) had relative success applying near-infrared (NIR) spectroscopy to identify sprouted kernels. However, this approach records the spectrum in a specific measurement point rather than the whole seed, thus failing to fully explore the information available (Wu, Zhu, Wang, Ma, & Wang, 2012; Xing, Symons, Hatcher, & Shahin, 2011). Thermal imaging, combined with machine learning, was successfully used by Vadivambal, Chelladurai, Jayas, and White (2010) to differentiate sound and sprouted kernels. Neethirajan et al. (2007) achieved accuracies above 90% using a soft X-ray system (1–100 nm). However, as pointed out by Singh et al. (2009), this kind of system may pose potential health risks to humans. Some groups are now investigating the possibility of using Terahertz imaging (wavelengths between infrared and microwave bands) as an alternative to X-ray systems (Jiang, Ge, Lian, Zhang, & Xia, 2016), but this is still an incipient technology.

Hyperspectral imaging (HSI) is another recent spectrum-based technique to be explored for analysing wheat kernels. This technique uses the same principles of spectroscopy, but it generates spectra for each pixel in an image, rather than for a small localized area (Barbedo, Tibola, & Lima, 2017). To the authors' knowledge, the first study to use HSI for wheat kernel analysis was carried out by Delwiche and Kim (2000). Since then, this technique has gained momentum and has been applied to several different wheat kernel classification and detection problems. Smail, Fritz, and Wetzel (2006) and Koç, Smail, and Wetzel (2008) were the first to use HSI for sprouting detection. Soon after, Singh et al. (2009) proposed a method to classify wheat kernels into sound, sprouted, and midge-damaged, achieving accuracies close to 100%. Xing, Hung, Symons, and Shahin (2009) used this technique to predict α-amylase activity in wheat kernels, obtaining accuracies above 80%. These authors continued to work on the problem for a few more years, focussing both α-amylase activity (Xing et al., 2011; Xing, Symons, Shahin, & Hatcher, 2010a) and sprouting detection (Xing, Symons, Shahin, & Hatcher, 2010b). More recently, Wu et al. (2012) used hyperspectral images to detect sprouting in whole ears of wheat, coming to the conclusion that under these conditions only severe sprouting is detectable. Although no new investigations on the use of HIS for sprouting detection have been published in the last five years, this kind of technique continues to find several suitable applications for wheat, including deoxynivalenol screening (Barbedo et al., 2017), protein content prediction (Caporaso, Whitworth, & Fisk, 2018), classification of contaminants (Ravikanth, Singh, Jayas, & White, 2015), detection of black tip damage (Armstrong, Maghirang, & Pearson, 2015), *Fusarium* detection (Ropelewska & Zapotoczny, 2018), among others.

Many methods exploring hyperspectral images apply Principal Component Analysis (PCA) to remove redundancy and make the data more treatable. This is the case for most of the references cited above. As powerful as PCA is, its use does not always lead to better results (Barbedo, Tibola, & Fernandes, 2015). More importantly, subtle particularities of specific bands that might be valuable in the classification may be lost in the process. Also, many of those methods extract several features to feed their classification scheme, increasing the chance that at least some features overfit the data and leading to biased results. In this context, the first objective of this study was to investigate how raw reflectance values could be used for sprouting detection, avoiding the use of PCA and other similar techniques. In order to simplify the requirements of a potential kernel screening system, this study also aimed to select a small set of wavelengths representative enough for sprouting detection.

The spectral responses associated to different wheat cultivars may vary considerable. Important differences were observed when hyperspectral imaging was applied to