Journal of Food Engineering 109 (2012) 38–48

Contents lists available at SciVerse ScienceDirect

Journal of Food Engineering

journal homepage: www.elsevier.com/locate/jfoodeng

# Shortwave infrared hyperspectral imaging for detecting sour skin (*Burkholderia cepacia*)-infected onions

Weilin Wang [a], Changying Li [a,*], Ernest W. Tollner [b], Ronald D. Gitaitis [c], Glen C. Rains [a]

[a] Department of Biological and Agricultural Engineering, University of Georgia, Tifton, GA 31793, USA
[b] Biological and Agricultural Engineering, University of Georgia, Athens, GA 30602, USA
[c] Plant Pathology Department, University of Georgia, Tifton, GA 31793, USA

ARTICLE INFO

*Article history:*
Received 2 May 2011
Received in revised form 15 September 2011
Accepted 2 October 2011
Available online 8 October 2011

*Keywords:*
Onion
Food quality and safety
Hyperspectral imaging
Sour skin
Log-ratio image
Support vector machine

ABSTRACT

Sour skin (*Burkholderia cepacia*) is a major postharvest disease for onions and causes substantial production and economic losses in onion postharvest. In this study, a shortwave infrared hyperspectral imaging system was explored to detect sour skin. The hyperspectral reflectance images (950–1650 nm) of onions were obtained for the healthy and sour skin-infected onions. Principal component analysis conducted on the spectra of the healthy and sour skin-infected onions suggested that the neck area of the onion at two wavelengths (1070 and 1400 nm) was most indicative of the sour skin. Log-ratio images utilizing the two optimal wavelengths were used for two different image analysis approaches. The first method applied a global threshold (0.45) to segregate the sour skin-infected areas from log-ratio images. Using the pixel number of the segregated areas, Fisher's discriminant analysis recognized 80% healthy and sour skin-infected onions. The second classification approach used three parameters (max, contrast, and homogeneity) of the log-ratio images as the input features of support vector machine (Gaussian kernel, $\gamma = 1.5$), which discriminated 87.14% healthy and sour skin-infected onions. The result of this study can be used to further develop a multispectral imaging system to detect sour skin-infected onions on packing lines.

Published by Elsevier Ltd.

## 1. Introduction

Sour skin is one of the most serious onion bacterial diseases that can affect most onion varieties (Mark et al., 2002). Under natural conditions, sour skin bacteria *Burkholderia cepacia* (*B. cepacia*) often infect onions through several different ways: the wounds on the shoulder area caused by rain or sand, the cutting wound at the neck area during the harvest, and other wounds in the neck due to the fallen foliage at maturity (Schwartz and Mohan, 2008). The sour skin infection typically happens on the surface or in the scales close to the surface layer (Fig. 1) and the top half (neck and shoulder) of the onion bulb is the high-risk area of sour skin. The exposure of onions to sour skin infection in storage rooms is disastrous because the pathogen may spread gradually and affect other disease-free onions, resulting in substantial losses. In addition, some strains of *B. cepacia* are human pathogens and have been deemed a leading cause of death in individuals with cystic fibrosis (Holmes et al., 1998). Therefore, it is necessary to identify and eliminate sour skin-infected onions during the grading process before they are placed in storage rooms or delivered to the fresh market. The screening of defective onions on packing lines is currently carried out by human visual inspection (HVI). However, it is difficult to detect sour skin-infected onions by HVI since symptoms of sour skin sometimes do not develop at the early stage and infection can remain latent until the environment becomes favorable (Gitaitis and Nischwitz, 2006). Furthermore, the performance of detecting sour skin by the HVI is prone to human subjectivity and inconsistency. These factors indicate a strong need for an accurate, nondestructive, and automatic method to discriminate sour skin-infected and disease-free onions on packing lines.

Several nondestructive methods were explored by researchers to detect defective and diseased onions. X-ray imaging has been studied for detecting internal voids and foreign inclusions in Vidalia sweet onions (Shahin et al., 2002). Since sour skin is a disease that also occurs in outer layers of onions, X-ray technology is not very suitable. Li et al. (2009) reported a method of using the gas sensor array to detect the sour skin by measuring headspace gas.

*Abbreviations:* DAI, days after inoculation; FPA, focal plane array; GLCM, gray-level co-occurrence matrix; HSI, hyperspectral imaging; HVI, human visual inspection; InGaAs, indium gallium arsenide; LCTF, liquid crystal tunable filter; LDA, linear discriminant analysis; MSI, multispectral imaging; NIR, near-infrared; PC, principal component; PCA, principal component analysis; RBF, radial basis function; ROI, region of interest; SNR, signal to noise ratio; SVM, support vector machine; SWIR, shortwave infrared.

* Corresponding author. Address: Biological and Agricultural Engineering, University of Georgia, 2360 Rainwater Road, Tifton, GA 31793, USA. Tel.: +1 229 386 3915; fax: +1 229 386 3958.

*E-mail address:* cyli@uga.edu (C. Li).

0260-8774/$ - see front matter Published by Elsevier Ltd.
doi:10.1016/j.jfoodeng.2011.10.001

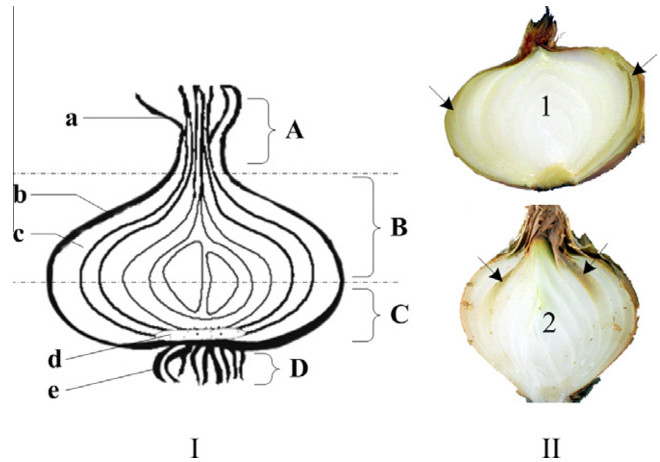


**Fig. 1.** I. Diagrammatic illustration of the parts of the onion bulb: neck dry tissue (a), outermost scale/skin (b), fleshy scale (c), root cap (d), outer root (e); neck area (A), shoulder/upper half of the onion bulb (B), and lower half of the onion bulb (C), and root area (D). II. Examples of sour skin infected onions at the outer scales (1) and the inner scales (2); the infected areas are marked by arrows.

It achieved 85% correct classification rate when six gas sensors were used. Although this technology showed promise to detect sour skin in onions, the gas sensors are more suitable in confined environment than on packing lines.

Near-infrared (NIR) spectroscopy is a nondestructive technique that has been widely used for quality evaluation and sorting of agricultural products (Williams and Norris, 2001). Birth et al. (1985) used NIR spectroscopy to predict dry matter content of intact onions, which showed that there were some correlations between internal quality of onions and their NIR spectra. The NIR spectroscopy has the potential to detect sour skin since the differences of chemical compositions between disease-free and sour skin-infected onions might be discernable to an NIR spectroscopy. However, the conventional NIR spectroscopy instruments can only measure one point at a time. Thus, the infection of onions could be easily missed if sampling points are not enough or the infection area is too small.

Extended from the conventional NIR spectroscopy technology, NIR spectral imaging has become important in nondestructive sensing of food quality and safety in the last decade (Wang and Paliwal, 2007). Spectral imaging allows the simultaneous collection of spatial and spectral information of the test object (Lu and Chen, 1998). A spectral image can be interpreted as a succession of images taken at a number of specific wavelengths, or a set of spectra on a 2-dimensional area. Spectral imaging techniques significantly enhanced the spectral diagnosis capability of the NIR-based technology from a single point to a 2-dimensional area. In recently years, NIR spectral imaging have been used to detect insect-damaged wheat kernels (Singh et al., 2009), bruises on pickling cucumbers (Ariana and Lu, 2008), bitter pits on apples (Nicolai et al., 2006), and to predict the constituent concentrations of single maize kernels (Cogdill et al., 2004). These applications have demonstrated the sensing capability of NIR spectral imaging for agricultural products. Since the NIR (780–3000 nm) covers a broad spectral region (ISO, 2007), the spectral region studied by this work (950–1650 nm) is termed as shortwave infrared (SWIR) in this article using the division scheme based on the response of the detector (Sensors Unlimited, 2011).

Spectral imaging can be specified to hyperspectral imaging (HSI) and multispectral imaging (MSI) based on the number of the spectral bands used ($n$). Generally, HSI ($n \geqslant 10$) is a useful tool to identify the optimal bands for developing MSI systems (Park et al., 2006). A main drawback of applying HSI on the packing line is that the large amount data from the hyperspectral images increases the complexity of data analysis and slows the speed for processing (Gowen et al., 2007). Different from HSI using hundreds of wavebands, MSI only uses a small number of key wavebands ($n < 10$) and thus it can obtain images that are much smaller than hyperspectral images. In addition, some MSI systems can acquire spatially-coherent band images simultaneously to reduce the image acquisition time (Kise et al., 2010). These factors make the MSI more applicable to packing lines than the HSI.

The overall goal of this study was to investigate the potential of using the SWIR spectral imaging to detect sour skin-infected onions. According to the infection mechanisms of sour skin, the top half (neck and shoulder) of the onion bulb is the high-risk area and was mainly investigated in this study. Specific objectives of this study were to: (1) compare the spectral characteristics of the disease-free (healthy) and sour skin-infected onions scanned by the hyperspectral imaging system in the spectral region of 950–1650 nm, (2) determine the optimal wavelength bands for discriminating the two classes of onions, and (3) develop classification models to distinguish healthy onions and sour skin-infected onions based on the images at selected wavelengths.

## 2. Materials and methods

### *2.1. Shortwave infrared hyperspectral imaging system*

An SWIR spectral imaging system (Fig. 2) was developed to acquire hyperspectral reflectance images of onions in the spectral

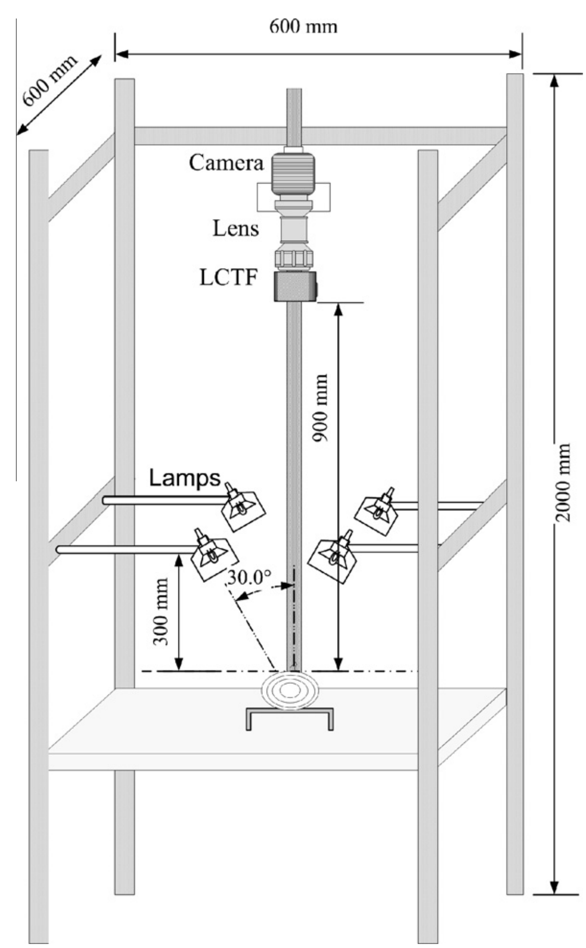


**Fig. 2.** The diagram of the hyperspectral imager and the lighting chamber.