Computers and Electronics in Agriculture 135 (2017) 289–299

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

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

Original papers

Field detection of anthracnose crown rot in strawberry using spectroscopy technology

Jinzhu Lu [a], Reza Ehsani [b,*], Yeyin Shi [c], Jaafar Abdulridha [b], Ana I. de Castro [d], Yunjun Xu [e]

[a] School of Mechanical Engineering, Xihua University, 999 Jinzhou Road, Chengdu, Sichuan 610000, PR China
[b] Citrus Research and Education Center, University of Florida IFAS, 700 Experiment Station Road, Lake Alfred, FL 33850, United States
[c] Department of Biological Systems Engineering, University of Nebraska-Lincoln, 3605 Fair Street, Lincoln, NE 68583, United States
[d] Department of Crop Protection, Institute for Sustainable Agriculture (IAS-CSIC), Cordoba, Spain
[e] Department of Mechanical and Aerospace Engineering, University of Central Florida, 12760 Pegasus Blvd., Orlando, FL 32816, United States

ARTICLE INFO

Article history:
Received 29 April 2016
Received in revised form 10 January 2017
Accepted 22 January 2017
Available online 24 February 2017

Keywords:
Strawberry
Anthracnose crown rot
Colletotrichum
Hyperspectral
Vegetation indices
Disease detection

ABSTRACT

Anthracnose crown rot (ACR) is one of the major diseases affecting strawberry crops grown in warm climates and causes huge yield losses each year. ACR is caused by the fungus *Colletotrichum*. Since this airborne disease spreads rapidly, detection at the early stage of infection is critical. The objective of this study was to investigate the feasibility of detecting ACR in strawberry at its early stage under field conditions using spectroscopy technology. Hyperspectral data were collected in-field using a mobile platform on three categories of strawberry plants: infected but asymptomatic, infected and symptomatic, and healthy. As a comparison, indoor data were also collected from the same three categories of strawberry plants under a controlled laboratory setup. Three classification models, stepwise discriminant analysis (SDA), Fisher discriminant analysis (FDA), and the k-Nearest Neighbor (kNN) algorithms, were investigated for their potential to differentiate the three infestation categories. Thirty-three spectral vegetation indices (SVIs) were calculated as inputs using selected spectral bands in the visible (VIS) and near infrared (NIR) regions to train classification models. The mean classification accuracies of in-field tests for the three infestation categories were 71.3%, 70.5%, and 73.6% for SDA, FDA, and kNN, respectively. These accuracies were approximately 15–20% lower than those of the indoor tests. The low accuracy (15.4%) of classifying healthy leaves in-field using the kNN model was possibly due to the training datasets being unbalanced. After the adjustment of sample sizes of each category, the accuracies of kNN improved greatly, especially for the healthy and symptomatic categories. Overall, SDA was the optimal classifier for both indoor and in-field tests for detection strawberry ACR. However, kNN performed better for asymptomatic leaves in the field in the case of balanced sample sizes of each category.

1. Introduction

During the 2014 crop year, more than 11,400 acres of strawberry were planted in the US (USDA, 2014b). Florida consistently ranks second in the strawberry production after California, with an increasing production rate (USDA, 2014a). However, a major series of diseases threatening strawberry production in Florida and other warm climate regions is those caused by the fungus *Colletotrichum* (Rodriguez and Redman, 2008), resulting in the disease anthracnose crown rot (ACR). The species *Colletotrichum gloeosporioides* is a fungal pathogen that devastates crop plants worldwide. Host infection involves the differentiation of specialized cell types that are associated with penetration, growth inside living host cells, and tissue destruction (O'Connell et al., 2012). The disease development is favored by warm temperatures and prolonged periods of wetness which are typical in Florida. Infected plants suffer necrotic crowns followed by sudden wilt and death (Peres, 2015). Infection by one pathogen may leave plants prone to infection or colonization by other pathogens, which aggravates the situation. All of these maladies make timely early-stage detection of ACR critical in strawberry production. Laboratory test approaches on plant tissue samples such as polymerase chain reaction (PCR), enzyme-linked immunosorbent assay (ELISA), and loop-mediated isothermal amplification (LAMP) are highly specific and sensitive to identify the disease (Bukhari et al., 2012; Chandra et al., 2015; Debode et al., 2009). However, conventional field scouting for

* Corresponding author.
E-mail address: ehsani@ufl.edu (R. Ehsani).

http://dx.doi.org/10.1016/j.compag.2017.01.017
0168-1699/

ACR in strawberry still relies primarily on visual inspection of the leaf color patterns and crown structures which is time- and labor-consuming and requires specialized skills (Debode et al., 2009; Tapia-Tussell et al., 2008).

Recent developments in agricultural technology have offered opportunities for non-destructive detection of plant diseases using spectroscopy (Sankaran et al., 2010). A visible near-infrared spectrometer (400–1000 nm) was used in the reflectance mode to discriminate sprouted and intact wheat kernels under laboratory conditions (Xing et al., 2010). The reflectance at 728 and 878 nm were used to classify sprouted and intact kernels, and the wavelength region above 720 nm was used to classify sprouted kernels of different levels of severity. The correct recognition rates of the intact, sprouted, and severely sprouted kernels were 100%, approximately 94%, and 98%, respectively. The ability of reflectance spectroscopy in three regions, ultraviolet, visible, and near-infrared, was evaluated indoors to determine the disease severity of tomato leaves infected with *Xanthomonas perforans* (Jones et al., 2010). The authors used partial least squares (PLS) regression, stepwise multiple logistic regression (SMLR), and combinations of PLS and SMLR to derive four predictive models. The results showed that the model established by SMLR was the best at predicting the disease severity with a root mean square difference of 4.9% and a coefficient of determination of 0.82. Recently, ground-level hyperspectral reflectance was used for in-field detection of plant nitrogen (Stroppiana et al., 2009; Vigneau et al., 2011; Zhao et al., 2005). Also, in-field hyperspectral sensing was used for wheat disease detection and differentiation (Muhammed, 2005). Spectral signatures of hyperspectral data were analyzed in leaves to differentiate sugar beet diseases (Mahlein et al., 2010). The spectral reflectance was measured in-field by a handheld spectroradiometer in the range of 400–1050 nm. The correlation coefficients values were highest ($r = 0.85$) in the visible region. This study also provided a basis for further classification methods of sugar beet diseases at different development stages.

Spectral vegetation indices (SVIs) from ground-level hyperspectral reflectance data can be used to estimate crop yield (Panda et al., 2010), detect variations in leaf area index (Brantley et al., 2011), and characterize agricultural crop biophysical variables (Thenkabail et al., 2000). They can also be used to detect and differentiate plant diseases (Devadas et al., 2009). Different diseases are often associated with specific physiological and visual changes of their host plants. Proper SVIs offer a great advantage in the mining of hyperspectral data. Hillnhütter et al. (2012) calculated nine spectral vegetation indices from hyperspectral data to investigate the influence of soil reflectance on the correlation between SVIs and leaf symptoms caused by nematodes and non-sporulating soil-borne fungi. The results showed that SVIs were closely correlated with leaf symptoms, but the correlations were influenced by soil reflectance. It was also found that the spectral angle mapper (Zarco-Tejada et al., 2001) method had potential in disease discrimination.

Most of the previous studies on detecting diseases caused by *Colletotrichum* are usually carried out by destructive methods (Chen et al., 2013; Debode et al., 2015; Raj et al., 2015). Few studies have reported using non-destructive methods for such an application under field conditions. The overall objective of this research was to investigate the feasibility of detecting ACR in strawberry at an early or asymptomatic stage under field conditions using spectroscopy technology. The specific objectives were: (1) to develop a field mobile data acquisition platform based on spectroscopy technology; (2) to evaluate various data classification models on differentiating healthy, asymptomatic, and early stage infected plants using selected SVIs; and (3) to compare the in-field system performance with laboratory test results.

2. Materials and methods

2.1. Spectroradiometer

A high resolution portable spectroradiometer (SVC HR-1024, Spectra Vista Corporation, Poughkeepsie, NY, USA) was used for collecting reflectance data in the range of 350–2500 nm, with spectral resolutions of less than or equal to 3.5, 9.5, and 6.5 nm for wavelength ranges of 350–1000, 1000–1850, and 1850–2500 nm, respectively. The spectral data were collected using a 4° field-of-view lens at a minimum integration time of 4 ms. In order to acquire the relative reflectance spectra of the sample, flat-field correction was automatically conducted by the proprietary sensor control software using Eq. (1). The raw spectra (R_{sample}) were calibrated by white ($R_{reference}$) and dark correction (R_{dark}). The white correction was acquired by a white reference panel (Spectralon Reflectance Target, CSTM-SRT-99-100 Spectra Vista Corporation, Poughkeepsie, NY, USA), and the dark correction was obtained by covering the lens with a light-proof cap.

$$R = \frac{R_{sample} - R_{dark}}{R_{reference} - R_{dark}} \quad (1)$$

2.2. Data collection

2.2.1. Field data collection

Field experiments were conducted around solar noon on a commercial strawberry farm located in Plant City, Florida, USA (Fig. 1). Five commercial strawberry cultivars commonly grown in Florida were included in this study: Sensation, Festival, Pilgrim, Radiance, and Sanibel. Four plots were planted for each cultivar in a randomized block design; each plot contained 10 plants grown in double rows, so there were 40 plants of each variety and 200 plants in all. Thirty plants of each variety were inoculated with *C. gloeosporioides* at early stages of growth. Several techniques for *Colletotrichum* disease inoculation were studied including dropping, spraying, and spot techniques (Denoyes-Rothan and Guérin, 1996). Since the strawberry plants cover a large area in our field experiment, the pathologists conducted the inoculation by spraying the fungal solution (Chen et al., 2005b; Zhang, 2016). Considering the warm temperature (22–25 °C) in Florida during the cultivation of the strawberry plants, pathologists did not use any

Fig. 1. Strawberry cultivation fields in Plant City, Florida.