BIOSYSTEMS ENGINEERING 162 (2017) 20–29

Available online at www.sciencedirect.com

ScienceDirect

journal homepage: www.elsevier.com/locate/issn/15375110

Research Paper

# Discrimination of winter wheat disease and insect stresses using continuous wavelet features extracted from foliar spectral measurements

Jingcheng Zhang [a], Ning Wang [c], Lin Yuan [b], Fengnong Chen [a], Kaihua Wu [a,*]

[a] College of Life Information Science and Instrument Engineering, Hangzhou Dianzi University, Hangzhou, Zhejiang, 310018, China

[b] School of Information Engineering and Art and Design, Zhejiang University of Water Resources and Electric Power, Hangzhou, Zhejiang, 310018, China

[c] Department of Biosystems and Agricultural Engineering, Oklahoma State University, 111 Agricultural Hall, Stillwater, OK, 74078, USA

ARTICLE INFO

Article history:
Received 9 October 2016
Received in revised form
1 June 2017
Accepted 20 July 2017

Keywords:
Continuous wavelet analysis (CWA)
Powdery mildew
Yellow rust
Aphid
Fisher linear discriminant analysis (FLDA)

Discrimination of crop diseases and insect damages is a critical task in pest management. As a non-contact and non-destructive method, spectroscopy has been recognised as an efficient way for crop pest detection. In this study, an advanced spectral analysis method, the continuous wavelet analysis (CWA), was used to discriminate three common diseases and insect damages in wheat crop: yellow rust, powdery mildew and aphid. In this research, leaf spectra were measured in both infected and reference plots at early grain filling stage. An algorithm was developed based on the continuously decomposed wavelet scalogram to identify types and severities of the damages. Its sensitivity and discrimination capability to damages were evaluated. Utilising an overlapping strategy, a wavelet feature selection method was established to identify optimal wavelet features discriminate the damages. Then, the discriminant model was developed based on the Fisher's linear discriminant analysis (FLDA). A total of six wavelet features with a central wavelength varying from 430 to 930 nm and scale factors of 4–8 were identified. According to a k-fold cross-validation, the averaged overall accuracy of the developed discriminant model was 77%. The CWA-based spectral discrimination approach showed good potential to serve as a basis to develop in-field, real-time, multi-damage mapping systems.



## 1. Introduction

Crop diseases and insect damages account for 10–40% of yield loss around the world (Christou & Twyman, 2004; Oerke, 2006; Strange & Scott, 2005). As an alternative to conventional cultivation, precision agriculture aims to apply the right types and amounts of inputs at the right place and time. To protect crop from disease and insect damages, precise applications of fungicides at targeted plants in time can not only improve productivity, but also mitigate field contamination. To achieve

* Corresponding author.
E-mail address: wukaihua@hdu.edu.cn (K. Wu).

http://dx.doi.org/10.1016/j.biosystemseng.2017.07.003

**Nomenclature table**

| | |
|---|---|
| AH | Aphids |
| AI | Aphid index |
| ANN | Artificial neural network |
| Anth | Anthocyanin |
| ARI | Anthocyanin reflectance indices |
| Car | Carotenoid |
| Chl | Chlorophyll |
| Con | Continuous removal features |
| CWA | Continuous wavelet analysis |
| Der | Derivative transformed features |
| DI | Damage index |
| i | Decomposition scale index |
| j | Wavelength index |
| $f(\lambda)$ | Frequency spectrum |
| FLDA | Fisher's linear discriminant analysis |
| m | Number of scales |
| n | Number of wavelengths |
| NPCI | Normalised total pigment to chlorophyll index |
| OA | Overall accuracy |
| PLSR | Partial least square regression |
| PM | Powdery mildew |
| PRI | Photochemical reflectance index |
| P.'s a. | Producer's accuracy |
| U.'s a. | User's accuracy |
| Vis | Vegetation indices |
| $W_f$ | Wavelet coefficients |
| WF | Wavelet feature |
| YR | Yellow rust |
| $\alpha$ | Wavelet scaling factor |
| $b$ | Wavelet shifting factor |
| $\lambda$ | Wavelength |
| $\Psi(\lambda)$ | Mother wavelet |

this, it is important to detect and map the infections of plant diseases and insects in field. As a non-contact sensing approach, spectroscopy has shown a great potential in mapping in-field plant status with high efficiency. Prabhakar, Prasad, and Rao (2012) and Sankaran, Mishra, Ehsani, and Davis (2010) conducted a number of studies to identify appropriate spectral bands/features and establish detection models for plant diseases and insects. Yang, Cheng, and Chen (2007) found that the wavebands around 426 nm and 757 nm were the most sensitive bands for determining infestation severity of brown plant hopper and leaf folder in rice at the canopy level, respectively. Jones, Jones, and Lee (2010) identified that spectral responses at wavelengths around 750–760 nm showed high correlation with the levels of bacterial infection on tomato. In detecting rice leaf folder, Huang et al. (2012) found that seven spectral regions (at 503–521 nm, 526–545 nm, 550–568 nm, 581–606 nm, 688–699 nm, 703–715 nm, and 722–770 nm) were well correlated with the damage severity at leaf level, whereas the waveband of 747–754 nm correlated well with damage sensitivity at the canopy level. Apart from raw reflectance, various vegetation indices (VIs) were also used to describe the severity of diseases/insects damages. In detecting yellow rust (YR) in winter wheat, Huang et al. (2007) showed that the photochemical reflectance index (PRI) was correlated with the disease severity with a coefficient of determination ($R^2$) of 0.97. Riedell and Blackmer (1999) claimed that the normalised total pigment to chlorophyll index (NPCI) highly correlated with the concentration of total chlorophyll, thus, could be used to detect damage caused by green bug and Russian wheat aphids at the leaf level. Zhang, Pu, et al. (2012) conducted an extensive analysis on detecting powdery mildew (PW) damage in winter wheat at the leaf level. They examined the performance of three categories of spectral features (a total of 32 features) including derivative spectral features, continuous removal transformed spectral features and VIs. Their results suggested that with an optimal combination of these features, a partial least square regression (PLSR) based retrieving model could achieve $R^2 = 0.8$ on detecting PW damage. Cao, Luo, Zhou, Duan, and Cheng (2013) found that the area of the red edge peak response at around 680–760 nm was correlated with disease severity of powdery at the canopy leaf level. Wang, Zhang, Zhu, and Geng (2008) applied artificial neural network (ANN) to develop a method for estimating the infection stages of late blight of tomato plants. The $R^2$ in estimating disease severity ranged from 0.62 to 0.66. In monitoring cypress aphid based on space-borne hyperspectral data, Pena and Altman (2009) found that two anthocyanin reflectance indices (ARI) were efficient indicators to the damage caused by the aphid (AH). Besides, by analysing the spectral properties of wheat plants infested by green bug and Russian aphid, Mirik et al. (2006) proposed an aphid index (AI), which was proven to be highly effective in estimating damage levels for these insect infestations. In addition, several attempts have been made to incorporate those remote-sensing-based features into the development of ground-based instruments. Results from field tests showed that such systems could produce accurate disease detection to facilitate automatic site-specific spray with an error percentage of 5.1% (Moshou et al., 2011).

Despite the progress that has been made in identifying spectral bands and features for diseases/insects damage detection, some obstacles remain in transforming these theoretical methods into practical applications, e.g. to discriminate different diseases and insects. Given that different diseases and insects sometimes have similar damage mechanism and symptoms, discrimination among them based upon subtle spectral differences can be very challenging (Graeff, Link, & Claupein, 2006; Mahlein, Steiner, Dehne, & Oerke, 2010; Mahlein et al., 2013). Therefore, there is a need to develop robust approaches to improve the effectiveness of diseases/insects discrimination. Wavelet analysis is a simple, straightforward, and efficient signal processing approach that has been successfully utilised for information extraction from hyperspectral data (Bruce, Li, & Huan, 2002). Cheng, Rivard, Sánchez-Azofeifa, Feng, and Calvo-Polanco (2010) and Cheng, Rivard, Sánchez-Azofeifa, (2011) used the continuous wavelet analysis (CWA) to retrieve biochemical and biophysical parameters in plants. They claimed that the CWA-based wavelet features had a superior performance on retrieving water content of plants. The CWA method was also adopted to construct wavelet features for estimating the damage intensity of YR, PW and AH in winter wheat (Luo et al., 2013;