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Comparison between wavelet spectral features and conventional spectral features in detecting yellow rust for winter wheat

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ABSTRACT

Detection of yellow rust is of great importance in disease control and reducing the use of fungicide. Spectral analysis is an important method for disease detection in terms of remote sensing. In this study, an emerging spectral analysis method known as continuous wavelet analysis (CWA) was examined and compared with several conventional spectral features for the detection of yellow rust disease at a leaf level. The leaf spectral measurements were made by a spectroradiometer at both Zodaks 37 and 70 stages with a large sample size. The results showed that the wavelet features were able to capture the major spectral signatures of yellow rust, and exhibited considerable potential for disease detection at both growth stages. Both the accuracies of the univariate and multivariate models suggested that wavelet features outperformed conventional spectral features in quantifying disease severity at leaf level. Optimal accuracies returned a coefficient of determination (R^2) of 0.81 and a root mean square error (RMSE) of 0.110 for pooled data at both stages. Furthermore, wavelet features showed a stronger response to the yellow rust at Zodaks 70 stage than at Zodaks 37 stage, indicating reliable estimation of disease severity can be made until the Zodaks 70 stage.

1. Introduction

Yellow rust disease caused by the fungus *Puccinia striiformis* has a severe impact on the production of winter wheat worldwide. The epidemic of yellow rust may result in extremely severe yield loss and deterioration in grain quality (Singh et al., 2002). In order to prevent widespread infection, fungicides were applied in considerable amounts at high cost (Line, 2002); which caused problems of fungicide residue and soil contamination (Strange and Scott, 2005). To mitigate the problem of fungicide overuse and facilitate effective fungicide spraying in the field, real-time disease detection and mapping is a necessity. As a noncontact way of obtaining ground information in a continuous manner, remote sensing is proven to be efficient in crop status monitoring and yield mapping (Moran et al., 1997; Seelan et al., 2003). Among various types of remote sensing techniques, hyperspectral remote sensing is one of the most efficient ways to capture weak signals in the spectrum, given its high spectral resolution (Goetz et al., 1985). Hyperspectral analysis is widely and successfully applied to monitor the vitality and stresses of crops (e.g. leaf area index, pigments contents, crop diseases and pests) (Haboudane et al., 2004; Moshou et al., 2004; Oppelt and Mauser, 2004; Duveiller et al., 2011; Zhang et al., 2012a).

Based on hyperspectral data, many forms of spectral features have been proposed and are used for information extraction, including vegetation indices (VIs), derivative spectral features and continuous removal transformed features (Clark and Roush, 1984; Demetriades-Shah et al., 1990; Weng, 2011). The above conventional spectral features (SFs) are commonly used proxies in spectral detection of crop diseases. Moshou et al. (2004) successfully detected yellow rust in winter wheat based on the normalized difference vegetation index (NDVI), with a classification accuracy higher than 95%. Jiang et al. (2007) found that the sum of first derivatives within the red edge (SDr) and the green edge (SDg) had a high negative linear correlation with disease severity. Huang et al. (2007) used the photochemical reflectance index (PRI) to quantify the disease severity of yellow rust at both canopy and field levels. Devadas et al. (2009) examined ten VIs in discriminating three different types of wheat rust. Their results suggested that the anthocyanin reflectance index (ARI) and the transformed chlorophyll absorption and reflectance index (TCARI) were the most

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efficient SFs for differentiating the three rust types. In addition, based on the support vector machines (SVM) technique and 6 VIs including NDVI, simple ratio (SR), structure insensitive vegetation index (SIPI), pigments specific simple ratio (PSSR), ARI and modified chlorophyll absorption and reflectance index (MCARI), Rumpf et al. (2010) successfully identified the sugar beet disease at an early stage, with the classification accuracy up to 97%.

Apart from these conventional SFs, the continuous wavelet analysis (CWA) was an emerging method for spectral analysis and time series analysis (Mallat, 1999), which has been adopted in remote sensing spectra/image processing (Bruce and Li, 2001; Bruce et al., 2006; Cheng et al., 2010, 2011). Given that hyperspectral data vary in both amplitude (e.g. feature depth) and scale (e.g. feature width), the CWA is able to decompose such data at continuous positions and scales, which allows a thorough exploration over the spectrum (Li and Bruce, 2004; Rivard et al., 2008). In Cheng et al. (2010)'s study, CWA derived features were compared with a number of conventional SFs in estimating leaf water content (LWC). With a spectral dataset comprised of 31 plant species, the wavelet features produced a significantly higher accuracy than the conventional features, which suggests the capability of CWA in detecting the biophysical status of plants is superior to conventional SFs. However, given our literature review, the CWA technique has received little attention for use in disease detection. In our review, comparison between the wavelet SFs and conventional SFs in disease detection was lacking. Therefore, to determine whether the CWA technique is suitable for disease detection, its performance was examined based on a spectral dataset with a large sample size. The objectives of this study were: (1) to identify the appropriate CWA derived SFs in detecting yellow rust disease at a leaf level and (2) to compare the performance of those wavelet features with conventional SFs using both univariate and multivariate regression models.

2. Materials and methods

2.1. Study sites and materials

The experiments were conducted at Beijing Xiaotangshan Precision Agriculture Experimental Base, in Changping district, China (40°10.6′N, 116°26.3′E) during the 2010–2011 growing seasons. The cultivar of winter wheat was 'Jingdong 9843', which was susceptible to yellow rust disease. The soil at this site is a silt–clay loam. The average topsoil nutrient status (0–0.30 m depth) was as follows: organic matter 1.42–1.48%, total nitrogen 0.08–0.10%, alkali-hydrolysis nitrogen 58.6–68.0 mg kg^{-1}, available phosphorus 20.1–55.4 mg kg^{-1}, and rapidly available potassium 117.6–129.1 mg kg^{-1}. The experimental field received 200 kg ha^{-1} nitrogen and 450 m^3 ha^{-1} water, which was a recommended rate for this cultivar. The spray method was used for inoculating yellow rust spores to wheat plants, referring to the National Plant Protection Standard (Li et al., 1989). Two concentration levels of summer spores were applied to generate a gradient of infection levels of yellow rust, including 4 mg 100^{-1} ml^{-1} and 7.5 mg 100^{-1} ml^{-1} with a dosage of 5 ml spores solution per square meter. The recommended amount of fungicide to prevent the occasional infection was applied to the (uninfected) reference area that was not inoculated. Each treatment included a 220 m^2 area; totaling 660 m^2 for the disease inoculation experiment.

Based on the study of Cao et al. (2009), Zodaks 37 is important for implementing preventive operations such as fungicide spray, whereas Zodaks 70 is important for conducting yield loss assessment. Therefore, leaf sampling and spectral measurements were carried out at Zodaks 37 stage (April 29) and Zodaks 70 stage (May 23), respectively.

2.2. Data acquisition

2.2.1. Spectral measurement for leaf samples

At each sampling stage, the leaves were cut from the plants with scissors then immediately packed with ice bags and transported to a nearby indoor laboratory for spectral measurement. A total of 107 leaf samples consisting of 29 healthy and 78 diseased leaves were collected at Zodaks 37 stage (S1); 91 samples including 26 healthy and 65 diseased leaves were collected at Zodaks 70 stage (S2). At each stage, samples were randomly grouped for calibration and validation of models with a proportion of 60:40 percent.

Leaf spectra were measured by a FieldSpec® UV/VNIR spectroradiometer (ASD Inc., Boulder, Colorado, USA) over 350–2500 nm wavelengths, coupled with an ASD Leaf Clip at the front side of each leaf. Ten readings were recorded and averaged to obtain a spectral measurement for each leaf. The spectrum of a white Spectralon reference panel (99% reflectance) was measured once for every 10 leaf measurements. Leaf reflectance was transformed by dividing the sample radiance with that of the white Spectralon reference panel. A digital color photo was taken right after each spectral measurement with a white paper background for determination of disease severity.

2.2.2. Determination of disease severity

In this study, disease index (DI) was used for quantifying the disease severity that denoted the portion of disease pustules on the leaf and was estimated through visual inspection (Graeff et al., 2006; Luedeling et al., 2009). All samples were inspected by one investigator based on the digital photos to minimize subjective error. The DI value was estimated in steps of 5% within a range of 5–100%. Leaves with a pustule portion less than 5% were assigned to the healthy class due to the difficulty to accurately recognize them.

2.3. Analytical methods

2.3.1. Continuous wavelet analysis and features extraction

Wavelet analysis is a powerful signal processing tool that has been successfully applied to hyperspectral data for dimensionality reduction (Bruce et al., 2002; Kaewpijit et al., 2003). Recent studies demonstrated advantages of wavelet analysis to some more conventional methods in identifying plant species (Kalácska et al., 2007; Zhang et al., 2006) and in estimating forest biophysical parameters (Pu and Gong, 2004).

Wavelet analysis can be implemented as a continuous wavelet transform (CWT) or a discrete wavelet transform (DWT) (Blackburn and Ferwerda, 2008; Bruce and Li, 2001). The DWT is mostly used for feature reduction but a drawback is the difficulty in interpreting the output coefficients (Kalácska et al., 2007; Cheng et al., 2010). In contrast, the CWT wavelet coefficients are directly comparable to the original reflectance bands and can thereby provide interpretable information on shapes and positions of absorption features for leaf spectra (Blackburn and Ferwerda, 2008; Cheng et al., 2011).

In this study, the CWA was performed on the reflectance dataset of diseased leaves to extract a series of wavelet features for detecting yellow rust disease. A workflow of feature extraction using CWA was illustrated in Fig. 1, which includes continuous wavelet transform, generating of wavelet power scalogram, obtaining correlation salogram and identifying wavelet features by thresholding.

2.3.1.1. Step 1: Continuous wavelet transform. The wavelet transformation was the central process of CWA which convert each original spectrum to a set of coefficients on varied wavelengths and