A PLANT-BY-PLANT LEVEL REMOTE SENSING CLASSIFICATION METHOD FOR COTTON ROOT ROT BASED ON UAV PLATFORM

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Abstract

Cotton root rot (CRR), caused by fungus *Phymatotrichopsis omnivore*, is one of the most destructive cotton diseases in Texas. Once the plant is infected by CRR, it is very unlikely to be cured. However, a fungicide named Topguard Terra was proven efficient in protecting cotton from being infected by CRR. Previous research indicates that the CRR will reoccur at the same region as past years. Therefore, knowing the CRR-infested area is helpful to prevent CRR from appearing. The CRR-infested plants can be detected by using aerial remote sensing (RS). When an unmanned aerial vehicle (UAV) was introduced to a remote sensing research field, the spatial resolution of imagery data increased significantly and higher precision CRR classification was made possible. An algorithm based on the Superpixel concept was developed to detect and delineate CRR-infested areas in a cotton field at a plant-by-plant (PBP) level precision. The algorithm can detect healthy or CRR-infested single individual plants automatically based on multispectral or RGB images. Five-band multispectral data were collected using UAV to test the algorithm. The results indicated the proposed PBP classification has 93.52% overall accuracy, which is higher than other compared regional classification methods.

Introduction

Cotton root rot (CRR) is caused by the soil-borne fungus *Phymatotrichopsis omnivora*, which is a very destructive plant disease throughout the southwestern U.S. It was first observed in Arizona in September, 1928 (Neal, 1929). The fungus is a soil organism not restricted to living roots, but has an independent means of over-wintering and dissemination. The fungus is thermophilic and thrives in alkaline soils (pH: 7.5-8.5). Most infected plants are dicotyledonous. The fungus spreads through root contact between plants and growth of mycelial in the soil (Smith et al., 1962). The fungus usually kills the plant within ten days (Yang et al., 2014). If the disease occurs at the early stage of growth, the plants will die before bearing fruit. If it occurs late enough to allow plants to flower, the disease will reduce the cotton yield and lower quality of lint. Based on Yang et al.'s (2014) observation, the area of CRR infected increased 10%-50% through the season (August to September). Previous control practices are neither economical nor effective (Smith, 2004). However, because CRR happens at the same place as the previous year, it can be predicted.

It is almost impossible to get CRR infected information from the ground because of the irregular shape of infected areas and large amounts of infected area. As a result, remote sensing is a necessary technology to be applied in this research area (Yang et al., 2010). Taubenhaus et al. (1929) started to use remote sensing technology for the study of cotton root rot. The infected cotton field was photographed from an airplane with a handheld camera. Nixon et al. (1975) introduced color-infrared (CIR) technology into documenting the distribution of cotton root rot infection and detecting the effect of chemical treatment for root rot. Multispectral video imagery of cotton root rot was also evaluated (Nixon et al., 1987). Yang et al. (2015) used remote sensing associated with high precision global positioning system (GPS) technology to map cotton root rot. Both multispectral and hyperspectral imagery are able to equally accurately distinguish infected areas, but the 3-band multispectral is more appropriate because it is cheaper and more widely available (Yang et al., 2010).

Previous research (Yang et al., 2005) indicates that airborne multispectral imagery data is able to successfully detect the cotton root rot infected area in both dryland and irrigated fields. However, the resolution is not high enough to support plant level prescription map interpretation. The height of the sensor platform affects the collected imagery resolution (i.e., higher altitude reduces the resolution). There is no research about UAV-based remote sensing for cotton root rot delineation. The high resolution of UAV-RS imagery makes it possible to detect CRR-infection at plant level precision. New plant-by-plant (PBP) classification methods are proposed based on Superpixel and K-means algorithms.

Materials and Methods

Study sites

The study was conducted on a 0.36-ac dryland field (Figure 1) at Stiles Farm near Thrall, TX (Latitude: 30°35’28.46"N, Longitude: 97°17’33.03"W). It is in cotton-corn rotation and has history of CRR.

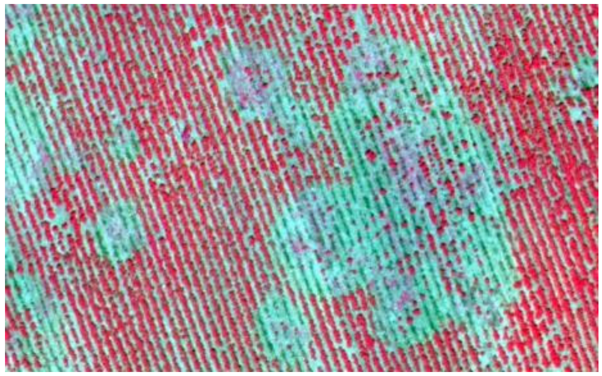

Figure 1. A dryland field at Thrall, TX was used for algorithm testing.

Multispectral image acquisition

On Aug. 20, 2017, image data were acquired with a MicaSense RedEdge camera (Figure 2) carried by a Tuffwing fixed-wing UAV platform (Figure 3). The Tuffwing main body is made of EPP foam with reinforcing carbon fiber spars. Including the sensor, the weight is about 2kg, and the wingspan is 1218cm.

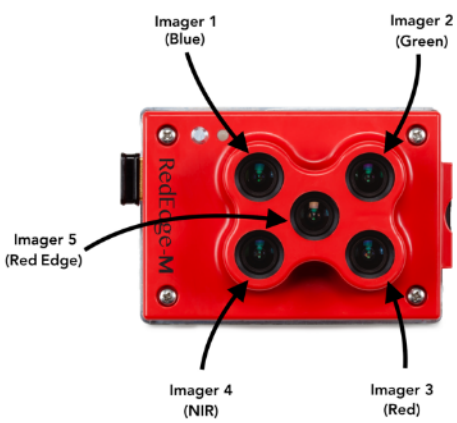

Figure 2. MicaSense RedEdge

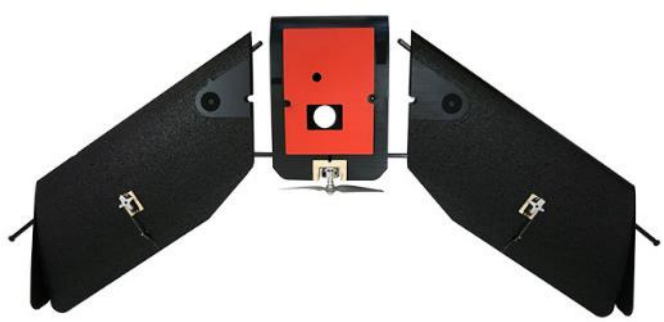

Figure 3. TuffWing UAV Mapper

The weight of the MicaSense RedEdge (MicaSense Inc., Seattle, WA, US) sensor is 150g and the size is 12.1 cm x 6.6 cm x 4.6 cm (4.8” x 2.6” x 1.8”). The RedEdge sensor collected 1280 x 960 pixels with 7.64 cm/pixel resolution when flying at 400 ft AGH in five bands: blue (≈ 475-500 nm), green (≈ 550-565 nm), red (≈ 665-675 nm), red edge (≈ 715-725 nm), and NIR (≈ 825-860 nm) bands.

Algorithm development

The PBP CRR classification algorithm used the concept of K-means clustering and Superpixel segmentation. The classification can be done automatically without training data.

Simple linear iterative cluster (SLIC) Superpixel segmentation was used to segment the raw multispectral image into small pieces based on the color and texture of origin image. Each piece is also called a superpixel, which is combined from hundreds of origin pixels of raw image. The digital number (DN) of each superpixel is the mean value of the origin pixels' DNs. The centroid of each superpixel was regarded as a potential seeding location. K-means was applied to a superpixel image and generate a regional classification map.

The gradient of the origin image was calculated to locate ridges of the cotton field. Made use of both the locations of potential seeds and the field ridges. PBP CRR classification map was generated.

Results and Discussion

The overal accuracy of the PBP classification map (Figure 4) was 93.52% with a Kappa coefficient of 0.7848. The error of commission and omission are 16.06% and 18.59%, respectively. In this case, the error of commission represents when healthy cotton plants are over classified as CRR, while the error of omission means CRR infested areas fail to be classified as CRR. The goal of this research is to generate a prescription map with small omission errors in CRR and to control a low level of CRR commission errors. Therefore, the map will avoid misclassifying CRR regions and prevent fungicide waste. It would be ideal to keep both errors of commission and omission at low level. In this research, the low error of omission is more important than low error of commission, because it represents less CRR areas were failed to be detected.

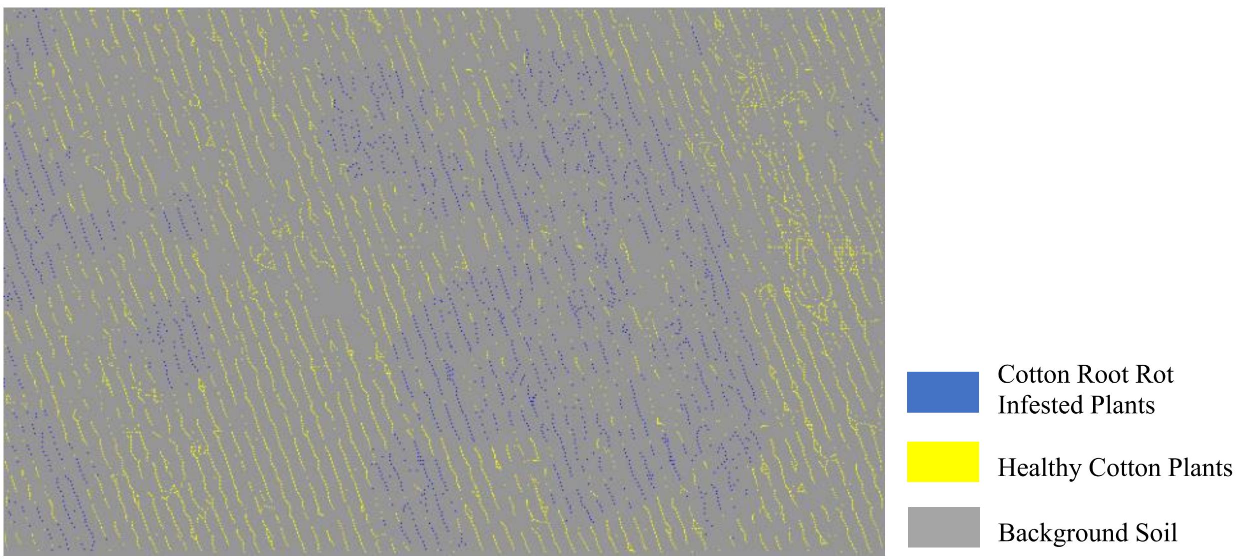

Figure 4. The final result of PBP classification

The PBP classification was also compared to other regional classifications including unsupervised, semi-supervised, and supervised classification. The comparison (Table 1) result indicated that the PBP has the highest overall accuracy and Kappa coefficient. Both error of commission and omission are at low level.

Table 1. The accuracy comparison between PBP and regional classifications

	Classification	Overall accuracy	Kappa Coefficient	Commission	Omission
Unsupervised classification	2-class K-means	78.60%	0.5106	50.43%	7.84%
	2-class ISODATA	83.95%	0.5979	42.30%	10.79%
Semi-supervised classification	10 to 2-class K-means	90.97%	0.6986	10.85%	34.95%
	10 to 2-class ISODATA	89.43%	0.6264	8.12%	45.38%
Supervised classification	SVM	92.02%	0.7587	18.50%	19.66%
	Maximum likelihood	91.71%	0.7498	19.38%	20.17%
Auto regional classification	KMSVM	87.60%	0.6307	29.98%	28.10%
	KMSEG	90.83%	0.7005	14.03%	32.54%
Auto plant-level classification	PBP	93.52%	0.7848	16.06%	18.59%

Summary

In this research, a method for using UAV high resolution multispectral images to detect CRR on plant-by-plant level was developed. The overall accuracy of the PBP classification method is as high as 93.52%. Compared to conventional regional classification methods, the PBP classification has higher accuracy and precision.

High resolution of imagery also introduces more noise to the classification. The noise including shadows of crops, bare soil between crops, and other unnecessary reflectance information impacts the classification result. In future, the noise removal will be considered as the primary direction.

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