DELINEATION OF COTTON ROOT ROT IN INDIVIDUAL CROP ROWS BASED ON UAV REMOTE SENSING

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Abstract

Cotton root rot (CRR) is a soil-borne fungal disease that is devastating to cotton crops in certain fields, predominantly in Texas. Research has shown that CRR can be prevented or mitigated by applying fungicide at planting, but fungicide application is expensive. The potential infected area within a field has been shown to be predictable, so it is possible to apply the fungicide only at locations where CRR exists, thus minimizing the amount of fungicide applied. Research also indicates that remote sensing with manned aircraft can be used to delineate areas of CRR infection. In this study, an unmanned aerial vehicle (UAV) was used to collect high-resolution remote-sensing images. Image-processing algorithms were developed to detect field rows from the images so that CRR vs. non-CRR classifications could be made at the plant-by-plant level. The current status of algorithm development enables identification of rows in cotton fields planted in straight lines.

Introduction

Cotton root rot (CRR) is a soil-borne fungal disease that presents a major problem to many Texas cotton producers. The fungus typically kills the plant within ten days of onset (Yang, 2014). When a plant becomes infected with CRR, plant death is usually the first symptom to be observed, so there is no practical way to cure infected plants. However, the likelihood of infection can be greatly reduced through the application of flutriafol fungicide at planting. To save on the cost of fungicide application, it is possible to predict the location of infected areas in fields and apply it on a variable-rate (VR) basis. Previous research indicates that the fungus resides deep in the soil and tends to stay in the same area of a field indefinitely. Studies have also shown that remote sensing with manned aircraft can be used to delineate areas of CRR infection (Yang, 2010), and that VR application of flutriafol at planting is feasible.

This study concerns using an unmanned aerial vehicle (UAV) to collect remote-sensing data at very high resolution. Such data may enable classification of individual plants and thus delineation of the infection on a plant-by-plant basis. Algorithms are being developed to produce a plant-level prescription map, which may enable VR fungicide application on a seed-by-seed basis at planting. The principal concept of the algorithm is identifying the rows first, and then scanning the entire field row by row to determine whether each individual plant is infected or not. As a result, the algorithm includes two main parts, row detection and plant-CRR classification down the row.

Materials and Methods

Data collection

Image data were collected with a fixed-wing UAV (Figure 1; Lancaster model, PrecisionHawk Corp., Cary, NC, USA). The UAV platform used was equipped with a three-band (green, red, near-infrared) multispectral sensor with resolution of 3.6 cm per pixel at 400 ft. above ground level (AGL). Such high resolution can provide enough image data for plant-by-plant level classification. Images were collected near the town of Rankin, in western Texas. The cotton field in the study had obvious and severe CRR infestation and had not had fungicide applied previously.

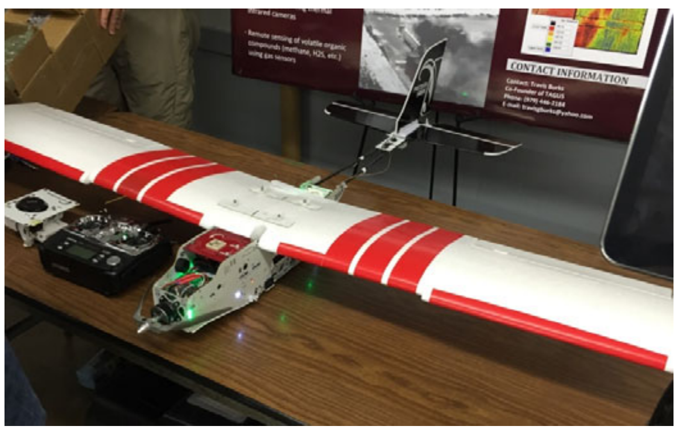

Figure 1. Lancaster fixed wing UAV platform.

Image processing

The Python programming language was used to develop the required algorithm for CRR image analysis. In crop row detection, the goal was to identify and locate the rows, converting them into single pixel-width lines. Those lines were then to be used as guides for subsequent disease scanning. Multiple image-analysis techniques were tested, but the ultimate row-detection process included Canny edge detection, Hough transform line detection, skeletonization, and noise removal. Canny edge detection is a multi-stage algorithm to detect edges in images. It includes Gaussian filter noise removal, gradient detection, non-maximum suppression, double thresholding, and hysteresis edge tracking. The Hough transform is an information extraction technique that is able to identify linear, circular and other types of shapes in images. The Hough transform results in a polygon instead of a line. As a result of these initial techniques, a color-infrared image (Figure 2a) is converted to a binary black-and-white image for further classification (Figure 2b). Skeletonization calculates the geometric center line of any shape in an image and reduces objects to single pixel-width lines and curves (Figure 2c). Final noise removal is used to remove image-processing artifacts and leave lines along the crop rows (Figure 2d).

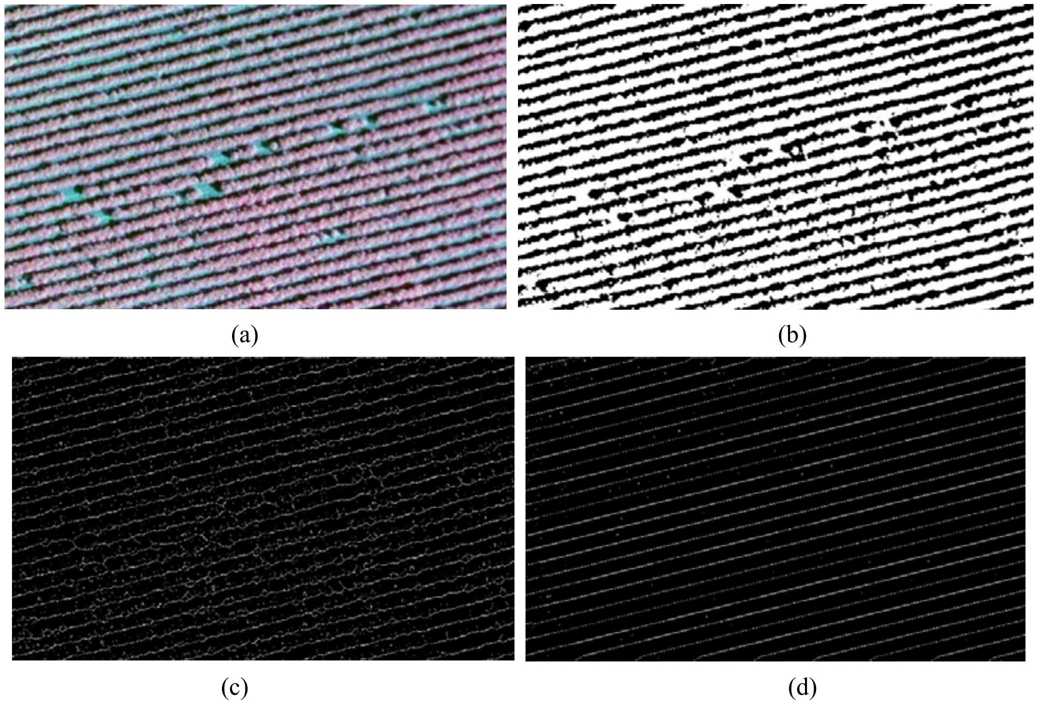

Figure 2. Image processing procedures for row detection.

Results and Discussion

As seen in Figure 2d, each line represents a row in the field clearly. In order to classify incidence of CRR as the research progresses, each line will be used as a guideline to scan each individual plant. While the image analysis procedure works well, some issues remain to be resolved. As can be seen upon careful viewing of Figure 2d, some individual noise pixels remain, and in some cases the lines are more than one pixel thick. Also, at the edge of an image, distortion of the lines appears because of the way the Skeletonization algorithm functions at the image edges. Further effort will be expended to solve these relatively minor issues. Additionally, while the overall algorithm works reasonably well at identifying straight rows, further development will be required to enable the algorithm to clearly detect curved rows.

Conclusions

The row detection algorithm is able to identify linear rows of cotton plants from UAV-based color-infrared images. These lines can serve as guides for plant-by-plant classification of CRR status. A few minor issues remain to be solved, and the algorithm must be enhanced to deal with curved rows.

References

Ge, Y. 2011. Remote sensing of soil properties in precision agriculture: A review. Front. Earth Sci, 5(3): 229–238

Gogineni S. 2004. Remote Sensing Input to GIS-Integrated Cotton Growth Model: Preliminary Results. Remote Sensing and Modeling of Ecosystems for Sustainability, Proceedings of SPIE Vol. 5544

Neal D. 1929. The occurrence of viable cotton root-rot sclerotia in nature. Science, New Series, Vol. 70(1817): 409-410

Neal D. 1935. Treatment of cotton root-rot with ammonia. Science, 75 :139-40.

Read J. 2003. Remote Sensing in Dryland Cotton: Relation to Yield Potential and Soil Properties. Ecosystems' Dynamics, Agricultural Remote Sensing and Modeling, and Site-Specific Agriculture, Proceedings of SPIE Vol. 5153

Smith R. 2004. South Texas cotton root rot draws study. Southwest farm press.

Sui R. 2008. Ground-based sensing system for weed mapping in cotton. Computers and electronics in agriculture 60: 31–38

Yang C. 2010. Comparison of airborne multispectral and hyperspectral imagery for mapping cotton root rot. Biosystems engineering 107: 131-139

Yang C. 2011. Assessing cotton defoliation, regrowth control and root rot infection using remote sensing technology. Int J Agric & Biol Eng Vol. 4 (4)

Yang C. 2012. Using spectral distance, spectral angle and plant abundance derived from hyperspectral imagery to characterize crop yield variation. Precision Agric 13:62–75

Yang C. 2014. Monitoring Cotton Root Rot Progression within a Growing Season Using Airborne Multispectral Imagery. The Journal of Cotton Science 18:85–93.