A Smart Vision System for Monitoring Specialty Crops

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***Abstract*—Precision agriculture involves observing the crop production process and applying appropriate actions to improve production efficiency. In this paper, a smart vision system is developed to monitor specialty crops which include fruits and vegetables. The smart vision system is composed of the image acquisition module and the image processing element. The image acquisition module is a modified point and shoot camera that could detect both visible and near-infrared wavebands, while the image processing element takes the multispectral image as an input and processes the images using a customized image processing algorithm for crop assessment. The smart vision system was tested using an experimental apple orchard, a commercial onion field, and a peach orchard. Results showed that the smart vision system was able to differentiate different watering input in the apple orchard, recognize the blossoms in the peach orchard, and detect the variation in the onion field.**

Keywords—Digital image processing; machine vision; remote sensing; specialty crops

I. INTRODUCTION

Specialty crop is a term used to define agricultural products that include fruits, vegetables, tree nuts, horticulture, and nursery crops [1]. Specialty crops account for about 40% of the total values of US crops. Agriculture is a labor-intensive operation, specifically for those producing specialty crops. For example, apple production involves task such as pruning, thinning, and harvesting, which are still done manually. The labor-intensive aspect of specialty crops poses a challenge to farmers, which is maintaining a sustainable crop production in the midst of a growing global population. Thus, farmers need to adopt new technologies that can support sustainable production [2].

One of these new tools available to farmers is precision agriculture, which is a site-specific technology. Precision agriculture relies on measuring field parameters and responding to the variability in the field [3]. The use of different sensors and global positioning system (GPS) allow the measurement of a field variable with site-specific precision. Precision agriculture has been used mostly for row crops including wheat and corn; however specialty crop growers have slowly applying its technology.

Remote sensing is one of the pillars of precision agriculture because of the capability of measuring crop variables without direct contact to the plants [4], [5]. Remote sensing is usually implemented using satellite or manned aircraft but the proliferation of cheap commercial unmanned aerial system [6] is very promising to specialty crop growers, specifically to those who have small acreage farms. The next task for the growers is the selection of an appropriate sensor that will be mounted on the UAS in order to conduct remote sensing.

In this paper, the development of a smart vision system that can be attached to a small UAS is described. The smart vision system is composed of an image acquisition unit and an image processing module. The image acquisition unit is a modified point and shoot camera that takes visible and near infrared bands, while the image processing module uses the visible and infrared values of the image to calculate vegetation indices that characterize field variability.

II. METHODOLOGY

A. *Unmanned Aerial System*

The unmanned aerial system used in this study is the DJI Phantom 3 professional quadcopter (Fig. 1). The DJI Phantom utilized a navigation controlled which could control the drone either manually or autonomously if interfaced with a tablet and the DJI Go application software. The DJI Go application was used to connect and interface with the controller in order to calibrate the UAS and to allow for GPS and waypoint navigation set-up. In addition to the DJI Go, DroneDeploy was used to collect field images. DroneDeploy is a cloud-based software which uses Google maps to construct a flight plan. Using DroneDeploy, the user can select the desired field, creates the path plan and the camera trigger points, and loads the waypoints to the UAS. After flying the field, the images were uploaded to the DroneDeploy website and create the orthomosaic of the field.

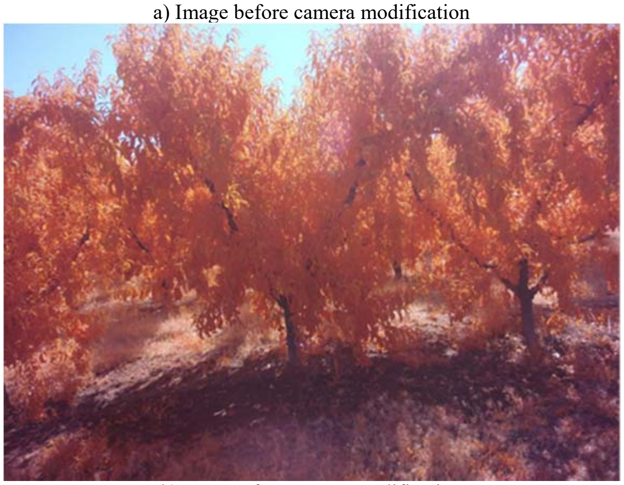
B. *Image Acquisition System*

In this study, the camera that comes with the Phantom 3 was used. This camera is similar to a point and shoot unit and it uses a CMOS sensor with 12.4 megapixels. The camera was modified to capture near infrared band centered at 750 nm, the green band, and the blue band.

The modified image (Fig. 2) shows the plants having a reddish hue as compared with the greenish hue that is observed with RGB images. The reddish hue is caused by the filter which allows near-infrared and replaced the red band. It is noted that plants reflect high near-infrared wavelength.

Fig. 1. DJI Phantom 3 flying over apple orchard.

a) Image before camera modification



b) Image after camera modification

Fig. 2. Sample images of before and after camera modification.

C. Image Analysis and Processing

An image processing algorithm was developed using the Matlab Image Processing toolbox to process and analyze the raw images captured by the smart vision system. The pre-processing involves the separation of the different bands and calculating vegetation indices that would be correlated with field variables such as irrigation, blossom characteristics, and soil nutrients. In this study, the enhanced normalized difference vegetation index (ENDVI) was calculated [7].

$$ENDVI = \frac{NIR + G - 2B}{NIR + G + 2B}$$

D. Specialty Crop Monitoring

1) Apple Orchard

The target field for the apple study was an experimental field with five different irrigation supplies: full sprinkler, 65% sprinkler, 50% sprinkler, full drip, and 50% drip [8]. The different irrigation supply was implemented using five tree rows. Each row has about forty trees and in each row, the five different irrigation supplies were randomly located. The small UAS was flown over the target field at about 400 feet with the five experimental rows in the middle of the region of interest in the image. The images were processed and analyzed using ENDVI and the irrigation variation were observed.

2) Peach Blossom

For the peach study, the peach orchard was observed during the blossoming period. There is an increase of photosynthetic activity during the blossom period which correlates with the fruiting capacity of the tree. Observing the blossom variation across the field could provide farmers additional information on optimal orchard management. The small UAS was flown over a commercial peach orchard at about 100 feet during the blossom period (spring season). The color properties of the blossom were compared with the background and an image processing algorithm to segment the blossom was developed.

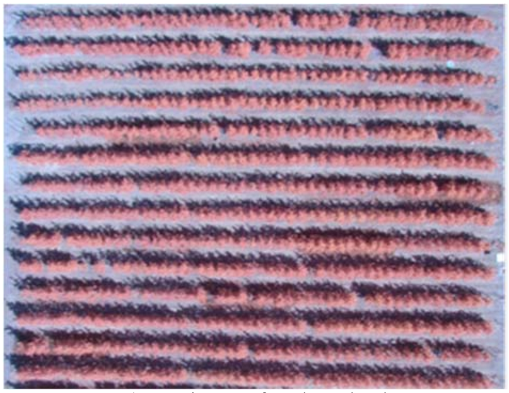
3) Onion Field

The onion study was an extension of using the ENDVI to monitor an onion field. Unlike the apple and the peach orchards, onions are ground crops. The small UAS was flown over an onion field at about 200 feet. The images were analyzed using ENDVI.

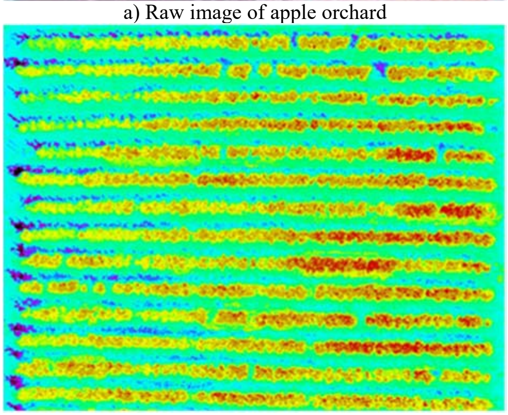
III. RESULTS AND DISCUSSION

A. Apple Orchard

There is a clear variation in the ENDVI false color image (Fig. 3). Both the full sprinkler and the full drip had high ENDVI values and the 50% deficit had the lowest ENDVI. This means that the ENDVI is effective in showing the effect of disrupting the water supply. ENDVI imaging in orchards could be useful in monitoring water input and it could also be combined with other factors such as disease infection and fertilizer input. Future research would study ENDVI usefulness for monitoring these parameters.



a) Raw image of apple orchard



b) ENDVI false color image of apple orchard

Fig. 3. Raw image and ENDVI image of experimental apple orchard.

B. Peach Blossom

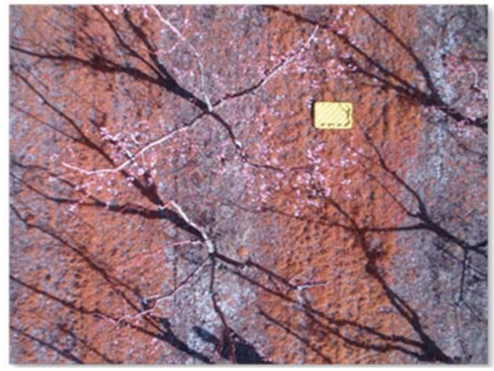
The image processing algorithm for blossom detection was able to detect the blossoms from the original images (Fig. 4). After thresholding the image, a morphological size filter was passed over the threshold image to remove 'salt and pepper' noise.

The blossom detection algorithm had a detection success rate of 84%. The detection of the blossom from each tree will be very useful for helping the farmers in managing their orchard. Future study would involve the calculation of blossom density per tree and correlating it with yield. Estimating the fruit yield from the blossom density will allow the farmer to efficiently plan fruit production early in the season.

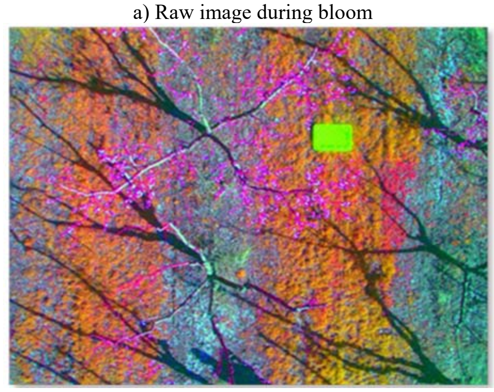
C. Onion Field

It was difficult to see the variation in the onion field in the original image. However, when the image was processed to calculate the ENDVI false color image, the variation was enhanced (Fig. 5).

The lower left side (Pride lane side) shows that it has lower ENDVI, which was caused by the type of soil in that part of the field. Clearly, the ENDVI showed the effect of the land type variation. Future efforts for the onion field would involve correlating vegetation indices with other factors such as irrigation and soil nutrient content.

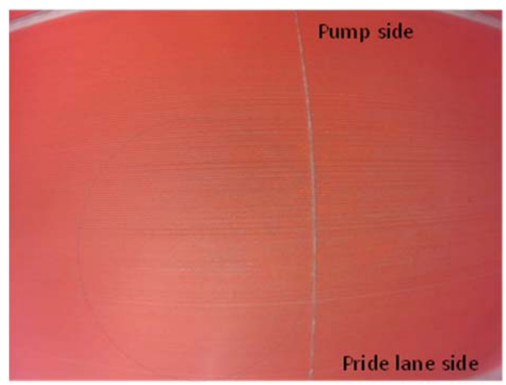


a) Raw image during bloom

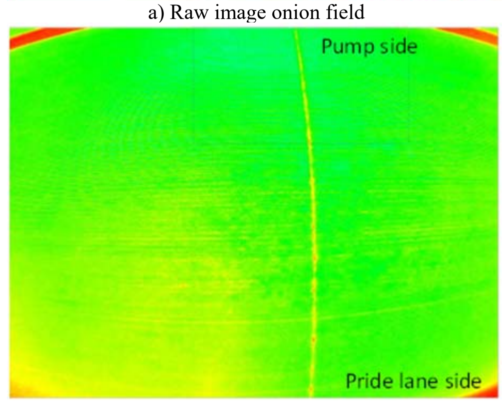


b) Processed Image during bloom

Fig. 4. Detection of peach blossom.



a) Raw image onion field



b) ENDVI false color image of onion field

Fig. 5. Raw image and ENDVI image of onion field.

IV. Conclusion

A smart vision system was developed for monitoring specialty crops. The smart vision system is composed of an image acquisition module and an image processing module. The image acquisition module is a modified point and shoot camera that allows visible and near-infrared bands to pass through, while the image processing element takes the multispectral image as an input and processes the images using a customized image processing algorithm for crop assessment. The smart vision system was mounted on a small UAS and was tested using an experimental apple orchard, a commercial onion field, and a peach orchard. Results showed that the smart vision system was able to differentiate different watering input in the apple orchard, recognize the blossoms in the peach orchard, and detect the variation in the onion field. This study shows the potential of the smart vision system to be a monitoring tool for specialty crop production.

Acknowledgement

This research was supported by the Idaho State Department of Agriculture (Idaho Specialty Crop Block Grant 2012 and 2014) and Northwest Nazarene University.

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