Drought Stress Image Processing
Summer Research Report

Austin Pursley

ECEN 491 – Dr. Xiaoning Qian

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Introduction

This was work was for a summer research project course I took, May-July 2018. It was loosely tied to someone else’s research project of using drones equipped with multiple cameras to analyze plants from above in a way that could be helpful for agriculture. My goal was to gather data on some plants that hadn’t been watered in awhile and find a way to determine how “thirsty” i.e. drought stressed they were.

Image Capturing

Over the course of a week I captured multiple visible light (VL) and infrared (IR) images a day of plants. There were 6 plants, 2 each of 3 species, ones that were watered over the course of the week and ones that were not. The hardware I used to capture the images was a Raspberry Pi and cameras on a bread board, held in place by a mini-vice and connected to my Windows Laptop with an ethernet cable. Power was provided by a portable power bank usually used for my phone. I also used a white poster board as a background as I thought this would make the image processing easier. For software I wrote a Python script to capture images that had features to stream-line process, like being able to preview images for acceptance/rejection. Both top and front facing images had been taken.

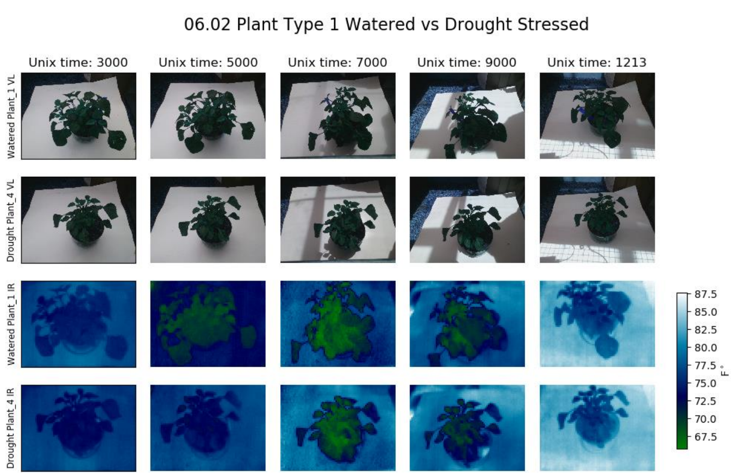

Figure 1: Pictures of the image capture set-up (top) and a collection of those VL and IR images (bottom).

Calibrating Thermal Images

The thermal camera used does not come calibrated for reading temperatures in Cº/Fº. The raw values given are a 14 bit number that usually read around 7000-8000s. In order for these numbers to be calibrated, the temperature of the camera at the time the image was taken was needed. When I was collecting the images I also collected ambient temperature readings and those are what I used as an approximation of the camera's temperature. Later I also took a thermal image of boiling and near-freezing water, whose temperature I knew by measuring them with a thermometer. So I had three camera-measured values (ambient, cold water, hot water) and their respective temperature readings in Fº. This was used to create a calibration equation. The values given out by the camera change with temperature so preferable this process would be done for several ambient room temperatures.

Finding Plant Region of Interest (ROI)

Given the raw images of the plants, I wanted to get a mask where the white area corresponded to the plant. So I tried to do this automatically with a simple image processing Python + OpenCV script. The overall idea was to apply threshold and morphology operations to find the plant area, e.g. for VL images find the large green area of the image by looking at the hue channel. However, one threshold value didn't work for all images so adjustments of that value had to be made to crop all the images. Therefore there was a less-than-ideal manual element for finding the ROI.

There was an issue where the front facing VL images could not be automatically processed because the pot that contained the plants was in the same range of color as the leaves. Therefore, the automatic process would also include the pot as part of the plant in the white mask. For time's sake that half of the dataset was not analyzed further, but some dutiful manual cropping of those images could make them useful.

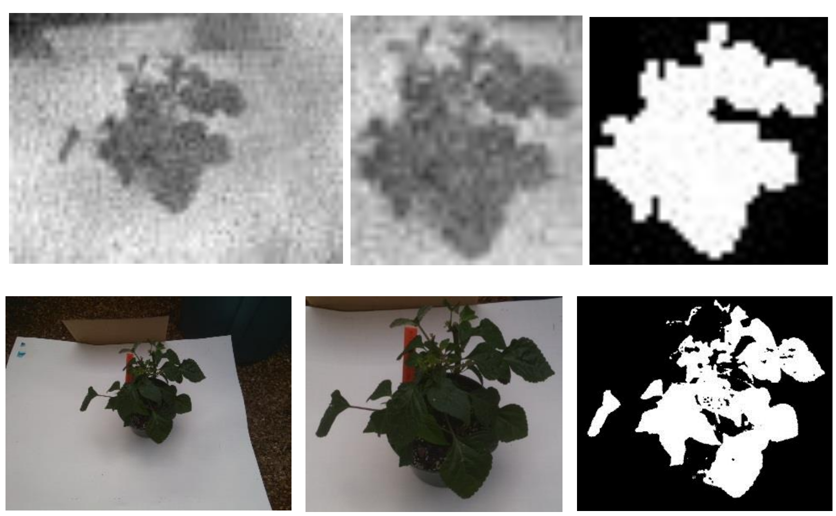

Figure 2: Example of image cropping step.

Image Features Over Time

With the ROIs I could find some image features. I first started with finding the mean and variance; for the IR imags it was just the temperature values as the image is just one single-channel, while for the VL images I analyzed the hue channel from the HSV color space. The expected realtionship was that the temperature would go up and the hue would go down torwards yellow for drought-stressed plants overtime. I plotted those two types of features and calculated correlation coefficients to visually and empiracally determine a possible relationship. For example, below you can see the graphs for VL and IR mean (the other plots can be found in the GitHub). The result was that there appeared to be no strong correlation (|r| > 0.7) of mean or variance with time for both VL and IR images. For thermal images, an additonal feature was looked at, the difference between the plant temperature and ambient temperature. However this also had a similar no correlated result.

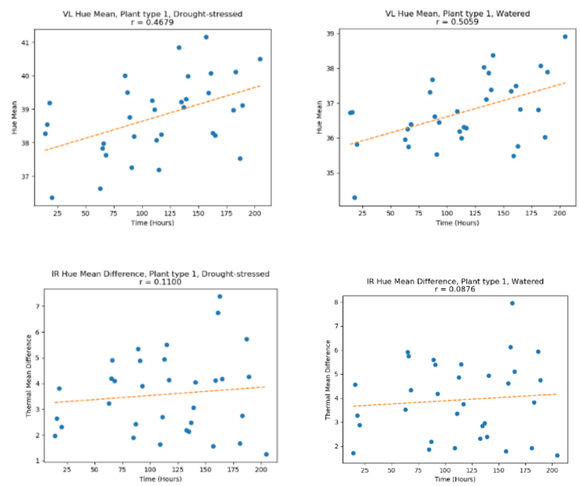

Figure 3: Plots for mean value, same plant type. Drought-stressed in left column and watered on right (see GitHub for other plots).

Conclusion and Future Improvements

For this project I got to physically collect all the images myself and then go on to anlayze those images to extract relevant features.Therefore is was an interesting hands-on look at the first few stages of a full data-analysis project. I think I especially got a lesson of how much care and thought has to go into creating a high-quality dataset for analysis. Altough there were plans to go on to applying machine learning, it was discouraged by the lack of correlation between time and the image features extracted. That non-ideal result naturally leads to thinking about future improvements. For one thing, sunlight in some images had an effect and care could be taken to shade the plants when collecting images next time. The length of the image collection perido could be longer as the drought-stressed plants showed no signs of yellowing or death yet. For thermal images, a potential cause of error could have been the calibration of the thermal images; a thermal camera with automatic temperature calibration could be used to address this. Finally, there are certaintly many more image features that could be extracted and explored when looking for relationships with drougth stress.