EECS-280 Final Project: Smarter Watering with Image Processing and Evapotranspiration

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1 Abstract

Smart irrigation techniques are becoming more common in agricultural environments. Sensor technology has become powerful and efficient enough to allow a network of sensors to be embedded into self improving irrigation systems capable of adapting to weather changes and specific local conditions [1]. This addresses the issue of water consumption relative to the environment. These systems are susceptible to local factors that prevent perfect irrigation such as a malfunctioning mote, blocked sprinklers, or coarse data points. Plant health data incorporated into the current processing pipeline can address this problem, by telling the system which areas need more attention. The focus of this research is to implement a non-invasive way to measure plant health and incorporate it into existing irrigation systems, improving its robustness by providing finer granularity data points.

2 Introduction

Evapotranspiration (ET) is a popular metric used in plant phenotyping and irrigation scheduling, however the drawback is that it requires consistent measurements on a tight interval. Existing smart irrigation systems that use this metric involve strict setup requirements, and those that do not, such as distributed or data-driven systems, have areas between nodes where moisture data is not available. This project will work towards a system that can build on top of exsting data driven models to provide higher granularity data of plant moisture to allow better irrigation scheduling. Existing image processing tools provide cleaner sections of plant for thermal data collection from an infrared camera. We conduct experiements with different image processing tools and share our findings, as well as discuss an alternative to data collection through a transfer function for moisture.

3 Related Works

[2] incorporates canopy temperature to estimate the crop water stress index (CWSI). The temperature data is collected using a two camera system. First, an optical camera is used to create a pixel mask that leaves only the area of interest. Second, the mask is applied to a thermal image where the canopy temperature can be collected. This system shows promise with accurate results using a gaussian mixture model (GMM) to determing the pixel mask, and correcting the error from using the same mask for two different cameras. The computational complexity of this model makes it less attractive for a low power system like the one we try to improve, which is why we decided to use a lightweight color filter in our implementation.

[3] is a document released in 1998 meant to provide a more accurate means of calculating crop water requirements. The original intent of the paper was to provide guidance to project managers, consultants, irrigation engineers, hydrologists, agronomists, meteorologists and students for the calculation of refer-

ence and crop evapotranspiration; more than 20 years later, the method is still used in commercial irrigation systems to calculate ET. The dependability of this method is the main reason for our decision to use it in our system. The reference ET value provided by the algorithm is independent of the crop, which could mean any result used to obtain ET for one crop, can be applied to other any crop, given that a crop coefficient exists.

4 Methods

4.1 Image Processing

Plant health imaging technology is still in the early stages of development, and thermal imaging techniques are proven to be more reliable and efficient than others [4]. Segmentation of target plants from its background has a major effect on the accuracy of temperature measurement and health predictions. Properly identifying plants from the background by combining inputs (IR Camera + regular camera) is an existing method of improving the accuracy of thermal plant imaging [2]. The decision to use OpenCV over other image processing libraries is due to it's widespread use in the computer vision community and ease of implementation [5]. Our system uses [5] to segment plants from an image for the creation of a bit mask. The mask is applied to a thermal image of the same location to reveal the areas of interest. The temperature data is used as input for the evapotranspiration equation from [3].

4.1.1 Segmentation

There are many different ways of segmenting regions of interest from an image, and the most lightweight method we found was color processing because it utilizes matrix operations on a simple pipeline. We compare the results of our color processing implementation to a neural network in Section 5. The basics of using color processing for segmentation is for every pixel in the image, differentiate the target object from the background. In our implementation, grass is the target crop whose major color is green, so we find the range of red, green, and blue values (RGB) that capture only the crop and nothing else. The range of RGB values is from 0 to 255, which mean ambiguities for pixels that lie between our target RGB value and the background RGB value will naturally occur. To make this task easier, we apply a contrast filter to the image to increase the difference between the target and background values to reduce the ambiguity between pixels. The contrast filter uses a method called contrast normalization, which subtracts the mean, standard deviation, and scaling factor from the orginal image. Depending on the input, the contrast should be adjusted differently, the same way the target range of RGB values is different for each scene.

4.2 Evapotranspiration

Temperature data provided by the imaging system is used as input to calculate water stress for the irrigation scheduler. The reference ET equation considers environmental variables that contribute to water loss, and only represent water loss in a particular setting, but generalizes for different crops. The crop coefficient from [3] is multiplies with the reference ET value to get the crop ET value, which gives the water loss for a crop in a particular environment. Variables needed to calculate the reference ET like wind speed, humidity, radiation, and vapor pressure are taken from local weather stations. This information is updated hourly and reduces the need for additional sensors on the systems with one base node with an internet connection, similiar to the system in [1].

5 Experiments

5.1 Segmentation Implementations

5.1.1 Comparison Subjects

To decide what image segmentation method to use, we compared two systems, one that represent a highly accurate system and another of a lightweight system. For our lightweight system we use a Python script which implements color processing and contrast normalization using [5]. In our highly accurate system,

Figure 1: Reference Evapotranspiration Equation

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma \frac{C_n}{T+273}(e_s - e_a)u_2}{\Delta + \gamma(1 + C_d u_2)}$$

- ET_0 = Reference ET (mm/day)
- R_n = Net radiation (MJ/m^2/day)
- G = Heat flux (MJ/m^2/day)
- U_2 = Wind speed (m/s)
- T = Temperature (°C)
- Δ = Vapor pressure (kPa/°C)
- γ = Psychometric constant (kPa/°C)
- e_s = saturation vapor pressure (kPa)
- e_a = actual vapor pressure (kPa)
- C_n = Constant (900)
- C_d = Constant (0.34)

Crop	**Kini**	**Kmid**	**Kend**	**Max Crop Height (m)**
Turf Grass (cool)	0.90	0.95	0.95	0.10
Turf Grass (warm)	0.80	0.85	0.85	0.10
Bermuda Hay	0.55	1.00	0.85	0.35

Table 1: Crop coefficients for each stage of growth, Kini (initial), Kmid (mid-season), Kend (late-season)

we implemented [6], a convolutional network originally intended for segmenting biological cells, that transfer well for segmenting fields with clear rows or patches, given a proper dataset. It is worth mentioning that datasets specifically for training image segmentation of agricultural fields in our context are rare. Instead, datasets for plant phenotyping such as [4] or satellite GIS like [7] are much more common, which influences our decision to test on images that include those categories.

5.1.2 Comparison Results

We found that both produce desireable results, and when weighed against the constraints of our system, the lightweight systems is more suited. The highly accurate system uses 31 million training parameters, takes 3 hours to train, and takes more than a minute to process one frame. In a system like [1] where computing power is limited, the lightweight system is more favorable, with a much smaller memory footprint of 1 MB and only a few seconds to process a frame. However, as computing power becomes more available, using a highly accurate system could pay off with it's robustness. Changing seasons or environments mean the lightweight system would require constant adjustments, where the highly accurate system can still operate with it's wider range of learned data and ability to be retrained. The results of color processing segmentation can be found in Section 7.

6 Future Work

This section is dedicated to discuss ideas that were planned for, but did not happen in Section 5.

6.1 Thermal Mask

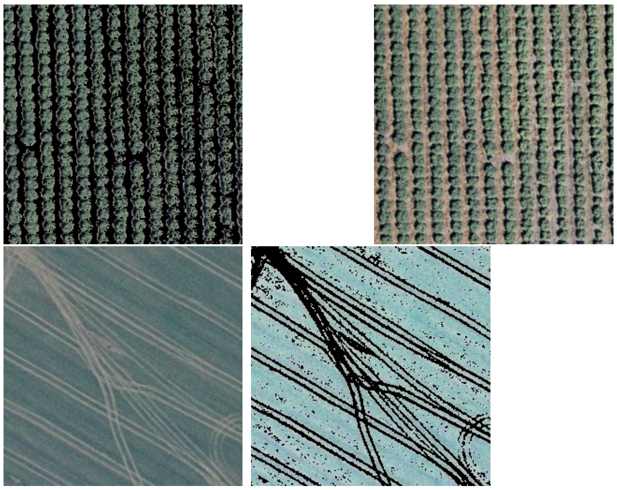
After a mask is created from the segmentation implementation, a thermal camera will use it to determine which regions are of interest. A possible study for this would be to measure the accuracy between the thermal camera system and a daily human measurement for irrigation scheduling. The main goal of this experiment is to prove the automated nature of the system as well as it's capability. As [2] points out, many crop fields still require people to measure temperature and moisture of their fields to adjust irrigation schedules due to limited supplies. An automated system that can measure temperature well enough for irrigation scheduling would remove this burden from the human.

6.2 Moisture Transfer Function

[3] discusses a relationship between water loss and moisture in it's calculation for ET, while [1] uses a

moisture model to relate the movement of moisure with time. In [1] the moisture model contributes to irrigation schdeuling, and takes as input measurements from moisture sensors at each sprinkler. There are regions between each node where moisture information does not exist and can negatively effect the moisture model, and eventually the irrigation schedules. A possible study that involves an above ground camera system to assist the below ground moisture sensors would solve potential problems stemming from regions without moisture data. The study would use moisture sensors as ground truth for training a model that predicts moisture from above ground thermal images. [3] mentions that the ground temperature is affected by the moisture below it, and the goal of the study would be to find a transfer function that represents this relationship. By varying the amount of moisure in the ground and gathering correlating thermal images, there should be enough data to find the relationship between below ground moisture and above ground temperature.

7 Segmentation Results



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