Image Processing Aerial Thermal Images to Determine Water Stress on Crops

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Abstract—Aerial imagery can provide meaningful information to farmers about the health of their crops. Infrared cameras can be used to provide temperature maps of fields which in turn can tell us about the water stress levels in individual plants in fields. In collaboration with Stanford GSB startup, Ceres Imaging, I worked on an image processing pipeline to better achieve this goal. My work focused around mosaicing images of a walnut field collected from a camera mounted on the crop duster and converting these images into a single meaningful temperature image that could be provided to a farm. The goal is twofold: to discover whether water stress can be seen in temperature images of walnut fields and whether this image processing pipeline can be fully automated. The foundation of this algorithm lies on correcting images for lens aberration and erroneous brightness anomalies, mosaicking images together based on a homography determined using SIFT and RANSAC and using a nonlinear equation to convert radiometric data to temperature data. Further work needs to be done on automating orthorectification, removing hot spots from temperature heatmaps and calibrating temperature images to show the contrast between water stressed and non-water stressed crops. Such corrections will enable us to make a final conclusion on whether water stress on walnut trees can be determined through aerial imaging and how automated this process will be.

I. INTRODUCTION

In recent years, the field of agriculture has sought to explore how sensor and data driven technology can revolutionize the industry by increasing yields and reducing upfront costs associated with pesticides, fertilizers and irrigation.

One area that is starting to be commercially developed is the use of low-flying aircrafts and UAVs to provide farmers with meaningful information about crop health. Thermal images taken with infrared cameras can be used to provide information about water stress levels within crops. [1] Water-stressed crops are noticeably warmer due to reduced evapotranspiration. Hence, differences in temperature can be exploited to identify water-stressed trees within an orchard.

For the project, I obtained a collection of thermal images from Ceres Imaging, a startup based out of the Stanford Graduate School of Business. This series of thermal images was taken from an FLIR A65 infrared camera attached to a wing of a crop duster (Figure 1). The photos are taken at approximate 610 meters overhead in a walnut field outside Stockton, California.

In the paper, I describe steps taken to develop a fully automated algorithm for processing thermal images taken from a crop duster mounted camera of a walnut tree orchard into a format that can be presented to farmers to be utilized in decision making. From this we hope to assess whether aerial photos of walnut fields can be used to determine water stress levels.
II. Image Processing: Methods Overview

The overall image processing algorithm took the following format. Each of the individual steps is discussed in further detail below:

Fig. 3. Image Processing Pipeline

1) Brightness Correction: Although most images had the same approximate average brightness, there were several images that were erroneously extra dark (Figure 4). Further investigation is currently being done as to why these dark images appear occasionally within the set of images. Although the reason for the dark images is unknown, prior to further steps such as mosaicking and conversion to temperature, they needed to be corrected. To do this, a running average pixel value over all pixels over all normal images was maintained. Anytime a dark image was detected based on mean pixel value, it was converted using the following algorithm.

\[
I_{cc} = I + (m_N - m_I)
\]  

The image was then histogram normalized based on the histogram compiled of all the normal brightness images to complete the color correction algorithm.

Fig. 4. Normal Brightness Photo versus Dark Photo

Fig. 5. Histogram of Normal Photos versus Corrected Dark Photo

Fig. 6. Corrected Dark Photo

III. Experimental Results by Processing Step

1) Brightness Correction: Although most images had the same approximate average brightness, there were several images that were erroneously extra dark (Figure 4). Further investigation is currently being done as to why these dark images appear occasionally within the set of images. Although the reason for the dark images is unknown, prior to further steps such as mosaicking and conversion to temperature, they needed to be corrected. To do this, a running average pixel value over all pixels over all normal images was maintained. Anytime a dark image was detected based on mean pixel value, it was converted using the following algorithm.

\[
I = \text{Erroneously Dark Image} \\
F = \text{Flat field Image, average image} \\
I_{ff} = \text{Image corrected for lens aberration}
\]

A. Lens Aberration Correction

The second step in the image processing pipeline was correcting vignetting in the image due to lens aberration. For flat field correction, a flat field image was created by taking the average of all the images collected that day. Given a sufficient number of photos and assuming that vignetting is consistent across images, the normalized average image should provide an accurate idea of vignetting. Each image was processed for flat field correction using the following formula:

\[
I_{ff} = \frac{I}{F_{\text{max}}}
\]
**B. Image Mosaicking**

For image mosaicking, I used open source library, VLFeat for SIFT feature extraction [3]. The code is adapted from a mosaic tutorial script provided by VLFeat [3, Applications: SIFT mosaic]. The basic algorithm for stitching two images is as follows:

1) Extract features from each image using vl_sift
2) Remove many to 1 matches
3) Use RANSAC to compute homography
4) If there are sufficient matches used in finding homography, stitch images together
   - Apply homography to map new image to the coordinate system of image 1
   - Increase the bounds of each image to account for expanded image
   - Stitch images together

In the initial algorithm, all the images were stitched in a single pass. However, the homographies between images collected from the first pass of the airplane and second pass of the airplane are not as accurate due to a smaller overlap between the two passes. As a result, there is significant error which is clear in the top right and bottom right corners (Figure 8). To reduce error propagation and increase the robustness of the algorithm, I stitched up to 10 images from a single pass. Consecutive images from a single pass had about 90% overlap so the homographies were quite accurate. Only 10 images were stitched at a time however to reduce the risk of waving as documented by Brown and Lowe. [4, p66]

These mini-mosaics were stitched into the final mosaic in a second pass of mosaicking. This provided to be quite effective in reducing skew error in the corners (Figure 9).

To correct for lens aberration and based on the idea that pixels at the center of an image are more likely to be accurate versus pixels close to the edge of an image, I implemented a simple center-weighting during image stitching as proposed by Szeliski [5, eq. 154]. However this blending method is not robust to slight misalignment errors in the mosaics.

\[
I_k(x) = \text{Value of pixel } x \text{ in image } k
\]
\[
w_k(x) = \text{weight of pixel } x \text{ in image } k
\]
\[
C(x) = \text{Output value of pixel in mosaicked image}
\]
\[
C(x) = \frac{\sum_k w_k(x) I_k(x)}{\sum_k w_k(x)}
\]
\[
w_k(x) = \arg \min_y \{\|y\| \mid I_k(x+y) \text{is invalid} \}
\]

**C. Orthorectification**

Orthorectification is one of the common challenges encountered in remote sensing image processing pipelines. Conventionally, orthorectification is done by mapping ground control points in aerial photos to those in an ortho-photo. However, there are not usually sufficient control points in images taken from cameras mounted on low-flying crop dusters and UAVs. [6]

Although significant time was spent on developing the algorithm for direct orthorectification, it became clear that based on calibration errors which were reported to be up to 5 degrees from the provider of the photos, that direct
orthorectification would not work in this setting. Furthermore, as long as aerial imaging as done through contract crop dusters, it is unlikely for us to obtain accurate, precise IMU readings.

As predicted, using SIFT and RANSAC across two modalities was also unsuccessful as the features are not consistent across the two modalities. As can be seen in figure 10, no accurate matches were made across the two modalities.

1) **Ground Control Point based Orthorectification:**
A second method of orthorectification was implemented mapping control points in the mosaiced image to control points in the ortho-image obtained from USGS. [7] Control points were matched using the MATLAB function, `cpselect` and then using the algorithm described here, [8], a projective transformation matrix was created.

Small errors in the relatively flat looking mosaic were further propagated in the transformation. It can be seen that difficult to discern kinks in straight lines in the mosaic are more visible in the orthorectified image. At this time, orthorectification using ground control points is undesirable given the human attention required for accurate transformations.

D. **Further Processing of Thermal Data**

The final step in the image processing pipeline is to convert the images taken with the infrared camera to temperatures which can be used to provide farmers with meaningful information about water stress levels. The equation below for converting 14 bit radiometric data to temperature data was provided by FLIR for use with the Ax5
camera systems. [9]

\[
R = 379702 \\
B = 1428 \\
F = 1 \\
F = -128
\]

\[
T_K = \frac{B}{\log \left( \frac{R}{(S - O)} \right) + F} \tag{5}
\]

\[
T_C = T_K - 273.15 \tag{6}
\]

\[
T_F = T_C \times 1.8 + 32 \tag{7}
\]

This step has not yet been implemented for the full mosaicked image given issues in consistent brightness across the images. Based on initial viewing, it would be prudent to calibrate the temperature based on ground truth readings. Unfortunately, temperature calibration will need to be done with close collaboration with individuals at Ceres imaging. For the initial scope of this project, it was not possible. However, it remains a future goal to fully determine how to convert the thermal mosaic into temperature data that makes water stress more visible.

Also, additional steps also need to be taken to remove bright spots due to exposed ground in the field which can distract from discerning water stressed trees from healthy trees.

IV. RESULTS AND DISCUSSION

At this time, there are several weaknesses in the process because meaningful conclusions about the usefulness of this photo can be determined.

Further investigation into why certain dark images occur and why there is inconsistent lens aberration needs to be determined. If aberration is solely in the corners, images will need to be cropped prior to mosaicking and further overlap between passes will be required to mosaic images.

If brightness variation across images is not resolved however, meaningful thermal mosaics cannot be determined as the scale of apparent temperature variation will not be consistent across the entire mosaicked image.

Although orthorectification proved to be a major challenge, the challenges encountered did not cripple the overall goal of providing a meaningful, flat-looking image at this time. In this pilot, the images were able to be successfully mosaicked and the final image appeared to the untrained eye to be relatively flat. However, this is not a robust resolution. During commercial deployment, it is economically unfeasible to depend wholly on flight passes being perfectly horizontal. This is especially true as long as images are collected using contracted pilots in a field where precise horizontal flight is not a primary goal.

V. CONCLUSION

Although issues with orthorectification and conversion of thermal images to background-removed temperature images still exist, this implementation of an image processing pipeline shows promise, especially in the prototyping phase of the startup. It also provides hope that a solution based on open-source software for processing aerial images could be feasible for the goals needed especially when compared to the high costs of licenses for commercial software such as ENVI.

Through close collaboration with members of Ceres Imaging who have seen the walnut fields directly, it will be possible to more conclusively determine whether this imaging processing pipeline can extract sufficient details between water stressed and non-water stressed trees within the walnut field.

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VI. DISTRIBUTION OF WORK

All the work completed in this project was done by the author with feedback from Ashwin Madgavkar.
REFERENCES


