Multimodal remote sensing for enhancing detection of spatial variability in agricultural fields[1]

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Abstract: Detection of variability in agricultural fields depends on the spatial scale of the observed variable. Plant water status can be evaluated using thermal IR images that can provide valuable information on the water status, whereas visible RGB images can provide detailed information on the plants' color, which is not a good indicator of the water status. The informative mode (thermal IR images) has coarse resolution, as opposed to the excessive resolution of the less informative mode (visible RGB). In the present study, we present a method to enhance the information obtained from the thermal IR mode, by combining information from the visible RGB mode. We propose to un-mix the temperature of objects in the thermal images based on the information extracted from the high resolution RGB image.

Keywords: thermal un-mixing, end members, segmentation.

1. Introduction

One limitation in the use of thermal imaging for determining crop temperature and crop water status is that a pure sunlit canopy temperature is needed, and inclusion of shaded leaves and soil background can result in false detection of water stress. To overcome this, high spatial resolution thermal images were combined with images in the visible and NIR ranges (Moran et al., 1994; Clarke, 1997, Möller et al., 2007; Sela et al., 2007). Our group (Sela et al., 2007 and Möller et al., 2007) worked on high resolution images and used the images in the visible range to exclude soil and shaded leaves, resulting in high correlations between the calculated crop water stress index (CWSI) and stomatal conductance. One of the main conclusions from the last works (Sela et al., 2007 and Möller et al. 2007) was that the high spatial resolution (~500 pixels per leaves) enabled proper selection of sunlit leaves. But, the size of the image (6 X 6 m) was impractical for production of crop water status maps on a commercial scale. A much larger image size can be obtained from airborne photography and the increased pixel size introduces new challenge for extracting sunlit leaf temperature by un-mixing a mixture of sunlit and shaded leaves and bare soil that are included in a single pixel.

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Extracting sunlit leaf temperature can be performed by un-mixing. A leading approach for coarse resolution images is the theoretical Vegetation Index-Temperature (VIT) trapezoid (Moran et al. 1994). The VIT trapezoid is the shape obtained when plotting surface composite temperature (Ts) minus air temperature (Ta) as a function of fractional vegetation cover. Theoretically, all variations of crop water stress for different vegetation cover should fall within this trapezoid. Clarke (1997) further showed that the trapezoid could be divided into plant stressed and unstressed regions. The objective of the current work is to develop new un-mixing approach to extract sunlit leaf temperatures using multimodal images (visible RGB and thermal infra red). In the current work we introduce a method that is based on segmentation of high resolution RGB images to a number of end members, and subsequent computation of the end-members' temperature using statistical un mixing methods.

Spectral un-mixing is a common method used to extract pure spectral signatures of objects that are in a mixed environment, and their spatial dimensions are less than the smallest detectable object. In this common case, the additional information that must be provided is the end members, i.e. the characteristics of all the objects that are known to be mixed in that pixel. Based on that additional information, the proportion of each specific material in the pixel can be derived. Our case is different from the common un-mixing problem since we do not know the characteristics of the end members, i.e. we do not know the temperature of the objects that are in the same pixel with the sunlit leaf that we want to measure. Instead, in our case the end-members, their proportion on each pixel and their characteristics will be extracted from multimodal images (visible RGB and thermal infra red).

2. Materials and Methods

High spatial resolution images in the thermal and visible range were acquired around noon time in almond trees under five irrigation treatments in Kibutz Lavee, Israel. A 320x240 pixel microbolometer radiometer (FLIR, SC2000) was used for acquiring thermal infra red images, and a high resolution (8Mpixels) RGB camera (SONY F828) was used for the visible range. Images were acquired from a crane, about 20-25 m above the canopy.

The proposed un-mixing methodology consists of the following steps:

a) The first issue that has to be addressed is the co-registration of the images from the two modes (visible RGB and thermal infra red). In conventional systems, the images are produced by the same sensor and are therefore aligned. The use of two different sensors yields two images of the same scene from slightly different viewing angles, different optical lenses, and different acquiring sensors. Proper alignment of the two images is essential prior to the application of any un-mixing procedure. Alignment or co-registration of images is typically performed with images from the same source. In these cases, correlation based procedures usually yield satisfactory results. But images that carry different basic information cannot be co-registered using conventional techniques. We have developed methodology for multi modal image registration based on mutual information (Wachs et al., 2007). In this work we used mutual information for multi-modal image registration, and manually adjusted the registration were errors were found.

b) from high resolution RGB we obtained the proportions of sunlit and shaded soil and leaves. The RGB images were segmented and classified into 3 end members: sunlit leaves, sunlit soil and soil in the shadow. Segmentation was performed using the spectral angle mapper (SAM) and the pixels were divided into the 3 end members.

c) for each mixed thermal pixel a linear equation that describe the relationship between the temperatures of the objects and the mixed temperature is defined.

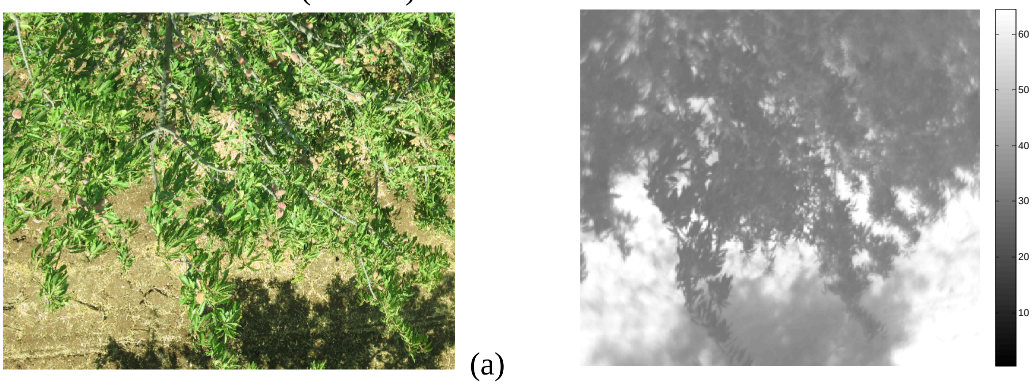
$$T_{i,j} = f_1 T_{ss} + f_2 T_{shs} + f_3 T_l \qquad (1)$$

where: $T_{i,j}$ is the temperature of the mixed pixel (i,j), f_1 and T_{ss} are the proportion and the temperature of sunlit soil respectively, f_2 and T_{shs} are the proportion and the temperature of shaded soil respectively and f_3 and T_l are the proportion and the temperature of the leaves respectively. The solution of the set of linear equations for all the pixels in the image, is the estimated temperature of the end members.

Thirty five images were analyzed, and the canopy temperature was estimated using the proposed un-mixing procedure. Leaf temperatures of pure thermal pixels were manually extracted, and compared to the leaf temperature computed with the proposed un mixing model. Paired t-test analysis was performed in Matlab®. (The Mathworks, US)

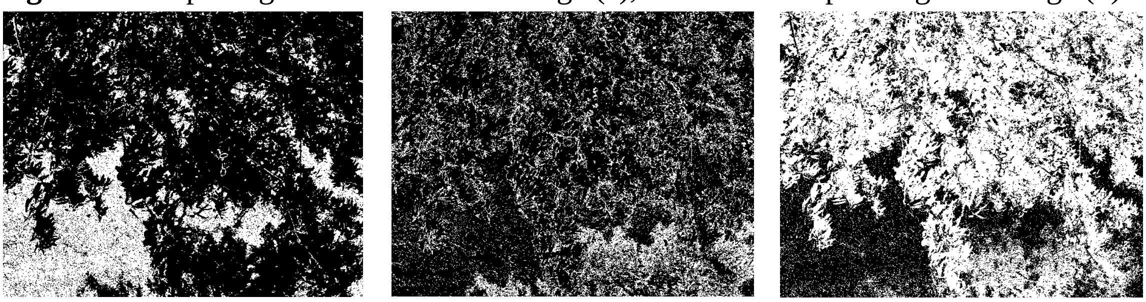
3. Results

Figure 1a shows a sample high resolution RGB image and 1b the corresponding TIR image. Figures 2a,b,c show the segmentation result to three end members, sunlit soil, shaded soil and leaves, respectively. Table 1 shows a comparison of the average leaf temperatures manually extracted for each irrigation treatment and the average leaf temperatures computed with the proposed un-mixing model. The average deviation is approximately 0.4 ^{o}C. Statistical paired t-test for comparison between the manually measured and un-mixing extracted temperatures showed that there is no significant difference between them ($\alpha=0.01$).



(a) (b)

Figure 1: Sample high resolution RGB image (a), and the corresponding TIR image (b).



(a) (b) (c)

Figure 2 Segmentation to three end members: (a) sunlit soil, (b) shades, and (c) leaves.

Irrigation treatment	Manually measured temperature [^{o}C]	Un-mixing extracted temperature [^{o}C]	Number of samples
High stress	33.7 (0.7)	33.3 (0.6)	9
Moderate stress	32.1 (1.0)	31.9 (0.9)	6
Low stress	32.7 (1.3)	32.5 (1.1)	8
Farmer's practice	30.4 (1.4)	30.2 (1.3)	4
No stress	28.8 (0.8)	28.9 (0.8)	8

Table 1: Comparison of the average leaf temperatures manually extracted for each irrigation treatment and the average leaf temperatures computed with the proposed un-mixing model. Numbers in brackets depicts the standard deviation of the sample.

4. Concluding remarks

The proposed algorithm successfully segmented the high resolution images into three end members and subsequently extracted their temperatures. This method can be used to produce high resolution water status maps. The information provided by these maps will be much more detailed that what the growers are used to - it will allow growers to adjust irrigation rates at high resolution (precision irrigation) when the irrigation equipment allows it – this means that a higher proportion of the orchard will be irrigated close to optimum, i.e. the highest, water use efficiency.

References

Clarke T. R. (1997). An empirical approach for detecting crop water stress using multispectral airborne sensors. *Hortechnology* 7, 9–16.

Moran M..S., Clarke T..R., Inoue Y., Vidal A. (1994). Estimating crop water deficit using the relation between surface-air temperature and spectral vegetation index. *Remote Sensing of Environment* 49, 246-263.

Möller, M., V. Alchanatis, Y. Cohen, M. Meron, J. Tsipris, A. Naor, V. Ostrovsky, M. Sprintsin, S. Cohen. (2007). Use of thermal and visible imagery for estimating crop water status of irrigated grapevine. *Journal of Experimental Botany*, 58(4):827-838.

Sela, E., Y. Cohen, V. Alchanatis, Y. Saranga, S. Cohen, M. Möller, M. Meron, A. Bosak, J. Tsipris and V. Orlov. (2007). Thermal imaging for estimating and mapping crop water stress in cotton. *European Conference in Precision Agriculture,* June 2007, Skiathos, Greece. Pages: 365-371.

Wachs. J., H., Stern, T., Burks and V. Alchanatis, 2007. Multi-modal Registration Using a Combined Similarity Measure, *12th Online World Conference on Soft Computing in Industrial application*, October 16-26, 2007.