AUTONOMOUS MULTI-SENSOR AND WEB-BASED DECISION SUPPORT FOR CROP DIAGNOSTICS IN GREENHOUSE

by

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ABSTRACT

An autonomous machine vision guided plant sensing and monitoring system was designed and constructed to continuously monitor plant related features: color (red-green-blue, hue-saturation-luminance, and color brightness), morphology (top projected canopy area), textural (entropy, energy, contrast, and homogeneity), Normalized Difference Vegetative Index (NDVI) (as well as other similar indices from the color and NIR channels), and thermal (plant and canopy temperature). Several experiments with repeated water stress cycles, using the machine vision system, was conducted to evaluate the machine vision system’s performance to determine the timeliness of induced plant water stress detection. The study aimed at identifying significant features separating the control and treatment from an induced water stress experiment and also identifying, amongst the plant canopy, the location of the emerging water stress with the found significant features. Plant cell severity had been ranked based on the cell’s accumulated feature count and converted to a color coded graphical canopy image for the remote operator to evaluate. The overall feature analysis showed that the morphological feature, Top Projected Canopy Area, was found to be a good marker for the initial growth period while the vegetation indices (ENDVI, NDVIBlue, and NDVIRed) were more capable at capturing the repeated stress occurrences during the various stages of the lettuce crop. Furthermore, the crop’s canopy temperature was shown to be a significant and dominant marker to timely detect the water stress occurrences. The graphical display for the remote user showed the severity of summed features to equal the detection of the human vision.
Capabilities and limitations of the developed system and stress detection methodology were documented with recommendations for future improvements for the crop monitoring/production system. An example web-based decision support platform was created for data collection, storage, analysis, and display of the data/imagery collected for a remote operator.
1. INTRODUCTION

Controlled Environment Agriculture (CEA) is a field which integrates engineering and horticultural technologies, enabling crop production within a controlled environment in regions that might otherwise be unfavorable for agricultural production. The CEA systems are typically controlled by measurement of a plant’s aerial environment (Boulard and Baille, 1993; Katsoulas et al., 2002) or root-zone environment (Dodd et al. 2000; Kirda et al., 2004) leading to the knowledge of the macro-environmental demands upon the plant. As technology becomes smaller, faster and cheaper, CEA systems appropriately desire to consider more factors of the plant’s environment for increased control. This level of control enhancement is coined precision agriculture which has become a popular concept, growing higher quality produce through minimizing resource usage (McBratney et al., 2005).

Some technologies exist to determine a plant’s health status. A main component is contact sensing which measures the micro-environment surrounding a plant (Liu et al., 2007; Takagi et al., 1998; Baille et al., 1994). The level of knowledge of the plant’s health has greatly improved, but contact sensing is cumbersome, labor intensive, and often plant destructive which is not practical for real-time commercial operations. Therefore, researchers have focused on the alternative, non-contact sensing techniques.

It has been known that plants are photosynthetically active within the range of 400–700 nm, falling within the human visual range (which is slightly larger, 380–740 nm). An educated human eye can detect (with plants) water stress, nutrient stress, insect
infestation, and even disease. But, the time and resources into educating humans for this level of precision is both lengthy and costly. Machines on the other hand can be used to imitate human actions, targeting the same purpose - to monitor plant health. Non-contact sensing, such as machine vision, extracts plant characteristics and when evaluated temporally, has the potential to detect trend changes in plants before the actual human visual detection can be made. This technology allows the perception of plants, targeting morphological (size, shape, texture), spectral (color, temperature, moisture), and temporal relationships (growth rate, development, dynamic change of spectral and morphological states) monitoring from the crop’s canopy (Leinonen and Jones, 2004; Ushada et al., 2007; Hendrawan and Murase, 2009; Story et al., 2010).

A leaf’s pigmentation is perceived by human vision and therefore can easily be monitored through the use of color cameras (Red-Green-Blue reflectance detection). A leaf’s pigments absorb light for photosynthesis and photomorphogenesis (Briggs and Olney, 2001) and it’s the reflectance of certain wavelengths that can be correlated to plant health. Hetzroni et al. (1994) evaluated lettuce nutrient deficiency (iron, zinc and nitrogen) reporting a reduction of the green component in the treated group compared to the control group and an increase of the red component due to the yellowing of lettuce plant after imposed nitrogen deficiency.

From the captured 2-dimensional color image, a plant canopy can be extracted from the background of an image. This extracted plant canopy as a monochromatic image represents the perceived canopy area and is coined as the plant’s Top Projected Canopy
Area (Ling and Ruzhitsky, 1996; Kacira et al., 2002; Teng and Li, 2003). This area can be measured over time and this trend would represent the plant’s growth rate. Similarly, the plant only region of an image is missing the depth perception and to compensate for this, textural parameters have been developed to better comprehend the missing 3rd-dimension. Probability density functions are used to evaluate the relationships of co-occurring pixel values (Ushada et al., 2007; Trias-Sanz et al., 2008). The specific textural values are in turn evaluated, helping to represent the change of the image’s textural characteristics to identify plant health.

Thermal cameras measure the radiance (typically from 7.5-13 µm) of surface temperatures in two-dimensions. With this technology applied to monitoring plants, plant and canopy temperatures can be extracted. From these values, various relationships can be inferred: crop water stress index (Idso, 1982), stomatal conductance (Jones, 1999), and leaf water potential (Cohen et al., 2005), each identifying mechanisms of the plants overall health. A healthy plant will absorb water from the root system and through transpiration, release water vapor and oxygen while absorbing carbon dioxide from the leaves. This process in turn maintains proper plant temperature and if the plant were to be under stress, this variance would be perceived by the thermal camera (Hetherington 1998).

Expanding on the pigmentation detection, researchers have developed the technology to evaluate the reflectance of plants in two-dimensions at a wide waveband range (300-1000 nm) split into very narrow intervals (2 nm) called Hyperspectral
cameras. With the use of these cameras, spectral signatures can be recorded, tracking relationships of waveband interactions to various plant responses. Kim et al. (2011) identified the total reflectivity of the plant water stress with apple trees. Their study concludes that high water stress correlation was found at the narrowband red-edge NDVI (705 and 750 nm) and the broadband NDVI (680 and 800 nm). In addition to plant pigmentation, the internal cellular interactions at a chloroplast level (Oxborough, 2004) can be tracked with fluorescent imagery as well as being capable of monitoring gene expression in real-time (McClung, 2006). The drawback to these imagery systems is that they are expensive, high maintenance, and require manual interactions which are not practical for real-time commercial applications.

For commercial production settings, it is advantageous to develop a real-time plant canopy health, growth and quality monitoring system based on a multi-sensor platform. This can be achieved through a robotic positioning system to accurately position multiple camera sensors, sampling the plant canopy, in turn using plants as “sensors” to identify their health status and needs. Such systems can be used to detect deviations amongst the canopy from normal development, identifying the location of the crop stress (i.e. nutrient deficiencies or diseases). Knowing that such systems do have value-added benefits, researchers have paved the way for the commercialization of such robotic machine vision systems to be implemented within greenhouse/growth chamber settings. The HortiMaX (www.hortimax.com) CropView system allows the grower to capture images of the plant canopy 24 hours a day, 7 days a week and time-stamps the
images to the collected greenhouse climatic data. The grower can only view the plant imagery, there is no extracted plant or canopy features to quantitatively determine overall plant growth and status. In other words, if there’s a plant-related problem, the trend of this issue is not identified until the grower visually identifies the problem, which is typically too late. Interest has also been increasing for high throughput phenotyping systems where such systems enable high-resolution mapping for genome-wide association studies and genomic selection models in crop improvement efforts. However, the costs and labor associated with the increased precision and accuracy must be minimized by automation, remote sensing, enhanced data integration and analysis (Cobb and DeClerck, 2013). LemnaTec (www.lemnatec.com) answers this need by providing several Scanalyzer products, monitoring the plant as a continuum by automatically positioning the plants under cameras for controlled imagery and analysis. The level of accuracy from the Scanalyzer promotes the high precision required for plant phenotyping on a broad level but this system is mainly for lab and greenhouse phenotyping settings, which is not practical for plant production on a commercial scale. To combat this disadvantage, LemnaTec offers a larger model, Scanalyzer Field, which offers a similar precision for field scale operations. The Scanalyzer Field acquires plant imagery in three-dimensions as well as associating the imagery with measured environmental conditions. This product does offer the complexity needed for the monitoring of plant production on a commercial scale except that there has been no literature on the system’s performance,
or how the camera system was able to deal with the shadows and uncontrolled light conditions.

The last component needed for any multi-sensor based platform would be the corresponding decision support system which manages the system, collects the data for storage, and displays the data in a format suitable for the grower. Combining the systems capability with a decision support system can assist with dealing and identifying the complex crop stress symptoms while increasing control of the overall plant growth environment. Power (2004) explains the importance of data-driven web-based decision support systems to remotely monitor, manage, organize, retrieve, and analyze large volumes of relevant data. This includes the display of model-driven analytical support providing tools for statistical analysis and simulation. Such support systems, with the inclusion of measured plant responses, can potentially improve the plant production’s resource use efficiency.

1.1 Problem Statement

Plants are continuously affected with stress (water, nutrient, disease, and pest infestation). To maintain a high productive plant means to lower or eliminate all stresses interfering with the plant. Except that the identification of the stress is difficult and challenging, since different plant stresses can exhibit similar features. Technology focusing on remote and non-contact sensing can provide in real-time an improved quantitative and qualitative measurement of various plant stresses. A machine vision
system consisting of multiple sensors can detect wavelengths in longer and wider ranges beyond human visual capabilities. For crop diagnostics, this would lead to the timely detection of the stressor and in turn improve overall plant health and quality.

Existing commercially available machine vision, crop monitoring systems are limited with their uses. As identified, if a product is capable of viewing the captured images of the crop production zone, then no image processing for extracting plant growth and health status is available. Likewise the reverse, if a product has plant feature detection, then the system is not capable for a commercial-scale real-time application. Additionally, to our knowledge, given an imagery plant domain region, there has been no method presented to autonomously identify the localization of an emerging stress.

1.2 Research Objectives

There has been increasing interest from research and commercial greenhouse operation settings for non-invasive and not contact real-time crop monitoring and diagnostic systems. The changes in plant reflectivity (Color and NIR), morphology, and thermal features can be indicative of plant disease or stresses. Therefore, there is a need for monitoring the crop and analyzing these features in real time, providing qualitative and quantitative information to the growers through a web-based decision support system. This in turn would help the grower prevent damage to the crops, manage resources optimally, better monitor all aspects of the plant growth, and improve overall production quality. The specific objectives of the study were:
1. To design and implement a computer vision guided plant monitoring system, which can be used for crop diagnostics within a greenhouse. Dealing with the uncertainty of environmental light characteristics using color, texture, crop indices, crop temperature, and temporal changes of the extracted features (Appendix A).

2. To evaluate the custom built multi-sensor based machine vision system’s capability to identify significant features separating the control and treatment from an induced stress experiment. Using these found significant features, timely identify amongst the plant canopy, the location of the emerging stress (Appendix B).

3. To design and develop a web-based decision support system collecting all greenhouse environmental data as well as the plant imagery to display the canopy results for the grower in real-time (Appendix C).
2. LITERATURE REVIEW

Experienced agricultural growers visually inspect plants daily for stress symptoms and from their analysis, can successfully detect the source of the stress. From visual inspection, information regarding the plant’s health and status has been detected which led to the conclusion of the stressor. The time and resources into educating humans for this level of precision is both lengthy and costly. Technology on the other hand, is becoming smaller, faster, and cheaper, modeling to imitate human actions. With the inclusion of technology, speed and accuracy are greatly increased and when applied towards monitoring plant health, technology can even outperform the human visual detection. Machine vision is the approach of technology imitating human vision, extracting plant characteristics but with improved capabilities, by analyzing these features temporally. As light energy illuminates a plant, some of that energy is absorbed by the leaves, some is transmitted through, and the rest is reflected (scattered away from the plant). It is the perception of this reflected light that machine vision systems use to evaluate the plant’s health and status.

Hetzroni et al. (1994) evaluated lettuce nutrient deficiency (iron, zinc and nitrogen) through machine vision. The lettuce plants were grown within a controlled environment, individually in containers filled with nutrient solution, aerated by an air stone. Image capturing was acquired by a digital charge-coupled device (CCD) color camera situated inside a photographer’s tent. The individual plants would be moved from the plant growth chamber to the tent for image acquisition. The tent was made of a highly
diffused white material with two external light sources to ensure the removal of shadows. Imaging occurred every two days, starting before the nutrient deficiency was imposed, continuing for about two weeks. Due to the variances with the image capturing system, from one imaging session to the next, frequent camera calibration was needed to ensure the consistency of the data. Cards of known color and size were used for the calibration. The study found that the treatment plant’s red component increased in reflectivity, green component decreased in reflectivity, while the blue component did not demonstrate a change. The authors pointed out that the nutrient deficient lettuce plants were more detectable at a younger stage than at an older one. Lastly, the authors stated that despite the high level of control in the image acquisition, there was still high variability with the analysis.

Ahmad and Reid (1996) evaluated the color features of water and nitrogen deficiency with maize plants, grown in open field agriculture. Plots of maize plants were divided into 3x3 m treatment blocks, covered by a rain shelter to control water levels. With the use of a split plot design, three water levels as well as three nitrogen levels were applied. 53 days after the maize seeds were planted, the first image was acquired from the experiment. Images continued from a sample plant from each experimental plot every 12 days consecutively until day 113 after planting. From each plot, a maize plant was dug from the ground and transported to a laboratory for imaging. Within each image of the plant, calibration cards were visible to identify known color and size. The study used a film camera to capture the spectral response of the plants. The photograph film was
processed the same day, creating slide images which were then converted into a digital image for analysis. The results from the study showed that from the Red-Green-Blue (RGB) color space, the red channel was capable of detecting water stress. But the Hue-Saturation-Intensity (HSI) color space was able to detect both the water and nutrient stress. The authors indicated that there was large variability in the results, suggesting that there is a need to develop a standard procedure for analysis.

When acquiring images of plants in situ of their environment, it is important to identify, within the image, the plant foreground from the background. Meyer and Neto (2008) examined the possibility of using the plant’s RGB reflectance as a marker for focusing on the plant foreground. The study focused on evaluating color vegetation indices with identifying the plant foreground (four different crops) with three background types (bare clay soil, weathered corn stalk, and fresh wheat straw). Digital images were acquired under natural sunlight at solar noon with the sun-light behind the camera to minimize shadows. The images were acquired approximately 1 m above the plants and a total of 180 images were analyzed for foreground extraction accuracy. Image processing was done with MATLAB scripts and compared to hand generated photoshop images. Three crop indices were generated: 1) Normalized Difference Index (NDI), 2) Excess Green (ExG), and 3) Excess Red (ExR). From each of the tonal resulting images, two threshold methods were used: 1) Otsu and 2) Positive Threshold. Otsu’s threshold assumes there are two classes within an image, a foreground and a background. Through statistical analysis of the image’s weighted histogram, a threshold is identified to be the
point where the smallest variance exists within these two classes. The positive threshold is to only identify regions within the tonal image that are greater than zero. From the results, the NDI method would result in an enhanced plant foreground and depending on the background, it was also enhanced. With Otsu’s threshold, the background could be suppressed with little added noise. Similarly, the ExG method greatly enhanced the plant foreground with little background noise. The Otsu’s threshold would include the already existent noise as the plant foreground. The ExR method would ignore the plant region foreground and instead would generally focus on the background. It was from the difference of these two excess methods that the author’s used to focus on the plant foreground, ExG – ExR. The resulting tonal image then had the positive threshold applied, resulting in a focused foreground similar to the hand generated image. The authors identified that more studies are needed to evaluate this plant foreground extraction method when challenged with inconsistent light and shadows.

From the extracted plant foreground, the resulting monochromatic image now represents the plant’s apparent morphology. Kacira et al. (2002) evaluated the perceived area of the plant, coined Top Projected Canopy Area (TPCA), under an applied water stress. Four experiments each containing six potted New Guinea Impatiens plants were grown and monitored within a walk-in growth chamber. Three of the six plants were classified as treatment and all were continuously monitored by a grayscale CCD digital camera, until human visual symptoms of the water stress occurred. Images were acquired from the plants every 15 minutes for 10 hours each day. A highly diffused screen was
placed between the artificial light source and the growing domain, to cancel any shadow occurrence. The background of the plant image was white enabling the extraction of the plant foreground to be possible through the use of a static threshold. The results showed that the TPCA feature was a good indicator for automated pre-visual detection but emphasized that more studies are needed to evaluate the approach with various other plants.

Foucher et al. (2004) applied a similar experiment, evaluating various morphological features of plants under water stress conditions. 40 plants of potted Forsythia, pruned such that all plants looked similar, were grown in a greenhouse setting. All plants were well watered at the start of the experiment and half of the plants had irrigation withheld, the treatment. The experiment ran for 6 days, acquiring a total of 26 images of each plant. For image acquisition, the plants were moved to a lab with controlled lighting and obtained by a RGB color camera. The author’s do not fully explain how the plant foreground was isolated, but their methodology suggests that they were able to isolate the plant foreground for analysis. From the extracted plant morphology, three features were used to measure the plant: 1) invariant moments, 2) fractal dimension, and 3) skeleton length. From the figures identifying the extracted features, it appears that the first invariant moment and fractal dimension are successful at identifying the separations of the treatment from the control. This occurs starting at the second data acquisition on day 5 of the experiment. The skeleton length feature does not appear to be as significant of a feature. These features are good examples to include with
phenotypic studies. The project does successfully use machine vision and plant morphology to identify the trend of plant health, but the authors were not clear on the system’s performance, the severity of the plants, or what improvements could be made to their system.

When machine vision systems are extracting features from a perceived object, the real-world object exists in a 3-Dimensional space. The 2-Dimensional image lacks the 3rd dimension. Therefore researchers have found ways to identify pixel relationships to denote the missing dimension. Pydipati et al. (2006) used a HSI color-based co-occurrence matrix to evaluate image texture on diseased citrus leaf samples. Citrus trees are grown in open field agriculture but select leaves are acquired and brought into the lab for analysis. In addition to sampling a healthy control leaf, three leaf diseases were sought after: 1) greasy spot (Mycosphaerella citri), 2) melanose (Diaporthe citri), and 3) scab (Elsinoe fawsettii). Forty samples of each of the four classes were collected. After the leaves were prepared, they were brought to the lab for individual image acquisition by a color CCD camera. The lab environment consisted of four 16 W cool white fluorescent bulbs with natural light filters and reflectors, located approximately 75 cm above the imaging plane (which was a uniform black surface). The camera was located in a similar proximity, directly above the sampling area. Image process was done through MATLAB and once an image was acquired of the leaf, Canny’s edge detection was applied to cancel any detected background noises. The image was then resized for ease of computation time and likewise, converted the RGB color space to the HSI. From each HSI color space
channel, co-occurrence matrices were created at 4 varying angles (0°, 45°, 90°, and 135°), and then 13 textural features are applied to each of the co-occurrence matrices. From each sample class, half of the extracted data were used as a training set and the other half was used as testing. The statistical analysis was done in SAS, using the discriminant analysis procedure STEPDISC. This created a model of significant features that were found to be more pronounced with identifying the four independent classes. Four models were created each focusing only on specific features from specific HSI channels: 1) HS, 2) I, 3) HSI, and 4) using all textural features from the HSI matrices. The results of this study identified that each of the models were successful with classifying the test data set but the strongest model (at 100% accuracy) was #4, the HSI model which considered all textural features. The authors suggest that improvement will be needed when attempting to execute the study in outdoor field conditions. Likewise, suggesting that the evaluation of a single leaf is not practical and should improve the approach to evaluate at the canopy scale.

Ushada et al. (2007) evaluated textural features from water stressed moss plants (*Rhacomitrium canescens* cv. Sunagoke) from the canopy scale. Eleven moss containers were grown in a growth chamber, using the container as the region of interest (ROI) for the acquired images. The image capturing was done in a lab setting with a color CCD camera supported by a tripod with external light sources (fluorescent lamp and an illuminating base plate). Acquired images occurred once a day from all eleven containers and for each image, the machine vision system calculated three canopy textural features
(Energy, Local Homogeneity, and Contrast). For the experiment, the moss containers were initially well watered but were left to dry for 17 days to generate a gradual degradation. Once an image was acquired, the RGB color space was converted to a normalized gray-scale image. Within the bounding ROI, co-occurrence matrices were created at 4 varying angles (0°, 45°, 90°, and 135°). The analysis was done with custom built software with Microsoft’s Visual C++ 6.0. The results showed that all three features had similar results, Contrast only differed by appearing to be the inverse of Energy and Local Homogeneity. By day 3 of the experiment, Energy and Local Homogeneity had the highest values and inversely, Contrast had the lowest values. After day 3, the values decreased or increased for Contrast and by day 8, the data values appeared to plateau. The authors pointed out from human visual inspection of the appearance that the plants started showing signs of water stress by day 3 and by day 8 there were severely stressed.

Technology has greatly increased from broad-band visual detecting cameras to cameras which are capable of detecting wide waveband ranges (300-1000 nm) split into very narrow intervals (2 nm). These Hyperspectral cameras are capable of detecting spectral signatures, tracking the relationships of waveband interactions to various plant responses. Xue and Yang (2009) investigated the spectral behavior between reflectance and chlorophyll content of four different green-leafy vegetables. The authors aimed at verifying the accuracy of chlorophyll estimated spectral indices (58 features gathered from the literatures) by quantifying the actual chlorophyll content. The four leafy vegetable varieties were 1) lettuce, 2) pakchoi (var. aijiaohuang in Chinese), 3) spinach,
and 4) pakchoi (var. shanghaiqing in Chinese). Five Nitrogen treatments were applied such that each plant had different levels of chlorophyll content and four replicates were performed. Four plants were grown in individual pots, watered daily, and located within a greenhouse. After the required growth period, two plants from each pot were sampled for spectral analysis and chlorophyll content. The reflectance was measured by a spectrometer which used an internal 7 W halogen lamp for illumination and 1 to 2 cm square pieces were analyzed for chlorophyll by a spectrophotometer. Statistical analysis was performed through ANOVA to evaluate the significance of leaf chlorophyll under different treatments and regression analysis to assess the relationships between leaf chlorophyll content and spectral variables. The results showed that most of the indices exhibited a strong relation with chlorophyll content, identifying that the normalized derivative difference ratio gave the best results. The authors pointed out that it would beneficial to expand the study to include various plants and analyze more than just the leaves.

Kim et al. (2011) identified the total reflectivity of the plant water stress with apple trees. Experiments were conducted within the greenhouse. Twenty potted apple trees were watered through drip irrigation, controlled to five different treatment levels with four replications, and data collection occurred weekly. The authors emphasized that the hyperspectral imagery can easily become distorted by illumination changes during image acquisition, requiring frequent calibration. Calibration was performed by measuring two references. The first being a dark reference, by covering the camera with a
dark cloth, and the second as a white reference, acquiring an image of a white board under ambient illumination. Thirteen different spectral indices were evaluated for plant stress detection. The experiment lasted only ten weeks, identifying there were only two index features that performed the best for water stress detection, the narrowband red-edge NDVI (705 and 750 nm) and the broadband NDVI (680 and 800 nm). The authors pointed out that reflectance differences between the stress and non-stressed were captured even when the human visual detection wasn’t made. There was no significant different between the three higher watered treatments and suggested that these three groups could be classified as well-watered. The last two treatment groups, likewise showed similar reflectance patterns and could be considered water stress groups. The authors have suggested that improved calibration procedures are needed if the hyperspectral imagery were to be used in open field conditions where frequent illumination changes occur.

Pacumbaba and Beyl (2011) evaluated five different macro-nutrient deficiencies in addition to a control to determine the spectral characteristics of lettuce plants. Two studies occurred where two plants for each nutrient deficiency were grown within independent plastic containers. One study was of lettuce plants grown in a growth chamber the other study was with the plants grown in a greenhouse. The nutrient deficiencies were imposed through modifying the Hoagland’s nutrient solution, replacing the targeted macro-element. After 90 days, three leaves were scanned from each plant. The reflectance readings were quickly taken around noon to minimize shadows. As hyperspectral imagery was being acquired, frequent measurement of a reference board
was performed to ensure accurate measurements. All statistical analysis was done through SAS, attempting to determine which wavelengths changed with respect to nutrient deficiency. The study found that lettuce plants grown in the greenhouse typically would produce lower chlorophyll concentrations causing the reflectance of the red-edge to shift to shorter wavelengths. The authors were not successful to discriminate specific nutrient stresses from the reflectance measurements, suggesting that refinement of the analysis is needed.

Zhao et al. (2007) compared vegetation indices derived from narrow and broadband red-NIR spectral data. To identify if broadband relationships exist with leaf area index (LAI) and canopy chlorophyll density (CCD). Four treatments of varying nitrogen levels with four replications were performed on cotton plants grown in open field agriculture. Data was collected during three growth periods of the cotton plant and only collected on cloudless days with solar angles around 50°, ensuring minimal effects from atmospheric conditions. The spectroradiometer was held perpendicular and at approximately 2.3 m above the canopy. The reflectance was measured as the ratio of measured viewed radiance to the radiance of a white standard reference panel. The procedure was repeated ten times to obtain the mean spectral data of each plot. On the same days the data was acquired, six cotton plants were harvested and weighed for leaf biomass. The leaf area index was measured as the ratio of green leaf area per sampled area and chlorophyll content, from the spectrophotometer absorbance, was measured in the lab. The authors have indicated that broad red-NIR bands have been found to be
sensitive to various vegetation parameters but were heavily influenced by background noises. The authors suggest that the broadband values lose critical information but with the use of spectral data that the vegetation indices could be improved. The results suggest that the red-NIR band position is more important than the band width when related towards LAI and CCD. The authors pointed that with the proper selection of wavebands from the spectral data, the limitations could be compensated.

From these identified spectral signatures, researchers have moved towards developing low-cost remote sensing systems focusing on these single signatures, creating devices to focus on specific stressors. Ryu et al. (2010) created a low cost reflectance LED-sensor, based on the broadband NDVI feature. The authors pointed out that LEDs could be used as photo detectors when configured in reverse, producing a small current. This current was found to be linear to intensity of the perceived energy. To measure this current, the authors attached an operational amplifier to two wired LEDs in parallel, effectively doubling the base current. The voltage outputs were read by a data logger once every 10 s and averaged over 30 minutes. The NDVI LEDs used were at the red peak (646 nm) and the near-infrared peak (843 nm). To ensure the LEDs perceive diffused light, the sensor housing was capped with a thick Teflon sheet. The authors created two sensor blocks, one to measure incoming solar energy and another to measure the reflectivity of the plant canopy. The measured canopy was annual cycles of grassland with hot dry summers and wet mild winters. After collecting data for a few years, the LED-based reflectance sensor clearly showed the phonological grassland cycles, showing
the abrupt decrease during the dry months and the quick increase after the autumn rainfall. When the sensor perceived NIR reflectance at its minimum, visual perception was correlated to the grass LAI at a minimum. The high temporal resolution was the LED sensor’s strength, regardless of weather conditions. The downside to this sensor is that the collected data is of a single point, not indicative of plant canopy phenology.

El-Shikha et al. (2007) improved the single sampling point, by sampling many points in 2-dimension space. The sensor package used in this study contained five detection sensors: 1) red (670 nm), 2) green (550 nm), 3) far red (720 nm), 4) near infrared (790 nm), and 5) infrared thermometer (8-14 µm). All sensors were perpendicular and positioned 4 m above the canopy, transported by a self-propelled cart. The scanning footprint was of about 1m. The experiment conducted was of broccoli with water and nitrogen treatments grown in open field agriculture. The site was divided into sixteen, 22x22 m plots, separated by 2 m wide strips of bare soil. The experiment consisted of a two-factor Latin square design, two levels of water treatment and two levels of nitrogen treatment of four treatments and four replicates. Initially, all plots were equally irrigated with water and nitrogen for 61 days after planting after which, the treatments would receive half-rate dosages. This was to ensure the plants were developed uniformly before the applied experiment. Data collection occurred approximately twice a week, starting just after solar noon to eliminate the shadow effect. From these reflectance sensors, four indices were calculated and with the temperature sensor, water deficit index was calculated. The authors pointed out that the canopy chlorophyll concentration index
(CCCI) was able to identify the nitrogen deficiency. The other vegetation indices were able to sufficiently detect the control and treatment differences but couldn’t differentiate between the two sources of stress. The authors suggest that combining CCCI with the other vegetation indices would help to provide input decisions between the water and nitrogen stress.

With the identification of 2-dimensional stress detection being useful for stress sampling, Xiang and Tian (2011) have developed an autonomous unmanned aerial vehicle (UAV) as an agricultural remote sensing system to provide field image collection through temporal monitoring of a turf grass field. A single multi-spectral camera was used, converting the RGB channels to R-G-NIR. All digital cameras are sensitive to the perception of near-infrared (NIR) (if the camera was not equipped with a near-infrared filter lens). The Agricultural Digital Camera (ADC) was developed by canceling the blue channel (with a yellow filter) from the RGB camera, allowing the blue channel to now only be sensitive to the near-infrared band. The other two channels, Red and Green, are likewise sensitive to the near-infrared, requiring frequent calibration of the camera to properly cancel the added noise. The UAV was successful to autonomously hover at a predefined waypoint 40 m above the ground for 20 minutes. For sampling, three UAV multi-spectral images were collected over a turf grass study area, approximately 60 m above the ground. The study area had sprayed total vegetation killer, effectively killing the grass in the designated locations. Immediately from the herbicide application, the camera was capable of detecting the vegetation loss through the calculated NDVI feature.
By the second sample two weeks later, the NDVI map shows complete vegetation removal and by the third sample (almost 3 weeks later), vegetation is beginning to return to the sprayed areas.

Machine vision systems have been capable of detecting reflectances of the plants, evaluating signatures of the emerging stress. With the lowering costs of technology, plants have been perceived in non-reflecting ways instead, evaluating the plant’s emittance of radiation. Through the use of thermal cameras, a plant’s temperature can be perceived. Jones et al. (2002) uses thermal imagery to study a plant’s stomatal conductance, concentrating on evaluation of the consistency and repeatability of measurements made under a range of environmental conditions. Measurements were made in the open field on mature grapevines with four blocks of four irrigation treatments. The treatment consisted of either being irrigated or no irrigation. The authors do not explain the length of the experiment, only identified the approach taken. Thermal images were obtained of the plant canopy as well as plant stomatal conductance was measured through contact sensors. Background temperature was identified as the radiative temperature of a crumpled aluminum foil. The result of this test identified the emissivity of the leaves were 0.95. Two types of reference temperatures were used. One of a vine leaf, sprayed with water as a wet reference and another covered in petroleum jelly. The second reference was Whatman’s filter paper, the wet reference was the paper maintained wet, the dry reference is the filter paper maintained dry. The results of the stomatal conductance analysis contained large variations. The authors pointed out that it
is important to avoid the inclusion of non-leaf material with the image analysis. They suggested using the wet and dry threshold temperatures as the range for which temperatures found outside are to be excluded. The authors also suggested to use real leaves attached to the plant, not filter paper or detached leaves, as the wet and dry reference. This is to ensure the same radiometric and aerodynamic properties of the canopy being studied.

Leinonen and Jones (2004) expanded on the thermography studies of leaf temperatures with the inclusion of visible imagery, using the visible imagery as a mask to identify the leaf-only regions of a plant. Experimentation was done with plants in a greenhouse setting and in open field. In the greenhouse experiment, broad bean plants were grown in 10 cm square pots with the treatment being a 2 day drought stress. Thermal and visual images were acquired from ten plants each from the control and treatment. The cameras were mounted on a tripod and included within the viewing domain were wet and dry plant references. With the open field experiment, images were acquired from mature grapevines with four blocks of four irrigation treatments. From both experimental sets, two thermal indices were calculated: 1) Crop Water Stress Index (CWSI) and 2) Stomatal conductance. The authors pointed out that using a wet and dry temperature range for temperature inclusion was not practical due to the possibility of plant stems being included within the temperature range. The results showed that the thermal indices were more accurate than previous studies. Suggesting it was because of the addition of visible imagery, to identify leaf location within the thermal images but the
authors pointed out that the manual image editing to identify the leaf locations were time consuming. The authors suggested a need for an automated approach to improve the analysis. One suggestion was to construct a rigid mounting system for the cameras where the geometry would be fixed, enabling the possibility of a standard overlaying algorithm for all situations. Lastly the authors identified that the use of a wet and dry plant temperature reference was not practical for field conditions.

Cohen et al. (2005) used thermal imagery for the estimation of water status of cotton under varying irrigation treatments. The study was to implement a possible variable rate irrigation system based on the modeling of estimated leaf water potential (LWP). The experiment studied cotton plants in open field with three treatment stress levels, induced by suppressing irrigation for 2, 4, 6 days respectively. The author does not specify the length of the experiment or the frequency of image acquisition, but stated that the thermal camera was mounted at a height of 5m above the ground. Five leaves from each treatment plot were sampled through contact sensing to measure the LWP. The authors stated that sampling the large number of leaves was not practiced and instead only sampled from a limited number of leaves. Due to this limited factor, a robust characterization of the crops water status wasn’t defined. The results show a strong relationship of canopy temperatures to LWP, suggesting that temperature could be a good indicator. The authors pointed that with the decrease in irrigation, soil temperatures were increasingly captured by the thermal camera, adding that spatial analysis from the thermal image is needed to be considered of the local variability.
3. PRESENT STUDY

In 2011, the University of Arizona’s Controlled Environment Agriculture Center (UA-CEAC) was awarded a Phase 2 NASA Steckler space grant, to continue the design and development of a Bioregenerative Life Support System (BLSS). The project was coined the Lunar Greenhouse (LGH) where multi-disciplines were joined, centering on using crop production in an enclosed system, researching the possibility for development of a permanent space colony. The inspiration for a plant-based BLSS is to provide fresh edible food, oxygen, and clean water to the space colonization crew (Drysdale et al. 1993).

The constructed LGH is cylindrical in shape, made of seven 2.2 m diameter rings. The design was envisioned to deploy collapsed and once arrived to the targeted destination, expand to the full cylindrical size of 5.5 m long (Sadler et al., 2009). Between each structural ring, water-cooled 1000 W, high pressure sodium lamps were positioned to provide the artificial lighting for the plants to use for photosynthesis. Between the first and last ring, 8 cable channels were used as a nutrient film technique (NFT) of providing water and nutrients to the plants. The LGH was designed as a multi-crop production chamber, based on NASA’s targeted crops (i.e. lettuce, tomatoes, sweet potato, strawberry, etc). As the plants grew in the LGH, water, nutrients and carbon dioxide were taken by the plants, in turn releasing oxygen and water vapor (through plant transpiration). The oxygen and water (condensation of the water vapor) were to be used
directly by the targeted crew. Likewise, the now available daily harvests of fresh fruits and vegetables for consumption.

Initial studies of the LGH chamber was a success, not only for the edible biomass, water, and oxygen production (for a hypothetical space crew), but also for stimulating the media, gaining the LGH chamber international recognition. Despite the success, a drawback was identified with the system. The plant’s roots would often clog the NFT channels. This clogging had two side effects: 1) nutrient solution would spill onto the chamber floor causing a flood if not timely caught and 2) plants located down-stream of the clog would exhibit signs of water stress, lowering the oxygen and water production. In a real-case scenario, astronauts cannot afford to have any disruptions with a life support system or require time for frequent repairs and plant recovery. Therefore, the phase 2 project added the design and development of a non-contact detection system to not only detect this water stress but to also identify other possible emerging stresses amongst the plant canopy. All of the plant imagery data was collected, analyzed, and displayed with the chamber’s environmental data through a web-based decision support system. This portion of the project, envisioned the possible application for the chamber to be in a real setting, having remote plant specialists monitoring the chamber to ensure maximum plant productivity for the astronauts.

Knowing that the implementation of this system is also desirable for Earth-based greenhouse plant production systems, it was decided to target towards that need. The LGH chamber has a constant light source with known shadows whereas the greenhouse
plant production system needs to consider variable light conditions and the incidents of shadows. By accepting the challenge to solve a more difficult problem, allowed the use of the derived methods to effortlessly be applied to lesser problems. Therefore the project aimed at developing a machine vision system within a research greenhouse at the University of Arizona’s Controlled Environment Agriculture Center, basing the plant production system and its limitations on the LGH system. The system was constructed to monitor the growth of lettuce plants (*Lactuca sativa* cv. Rex), within NFT channels. The applied experiments were to have the machine vision system detect water stressed plants by preventing nutrients from flowing to specified NFT channels.

### 3.1 Overall Summary

Appendix A and B of this dissertation, both present the manuscripts of the methods, results, and conclusions of both objective one and objective two respectively. Appendix C contains the results of the third objective, the development and functionality of a web-based decision support system, which was not presented as a manuscript. The following is a summary of the primary results of the research.

In Appendix A, the manuscript introduces the design and system components of the autonomous machine vision guided plant sensing system, located within a research greenhouse at the University of Arizona’s Controlled Environment Agriculture Center. The system was constructed to continuously, throughout the day, monitor lettuce plants growing in NFT channels. The system consisted of five main components including 1)
stepper motor–driven camera positioning system, 2) an image acquisition and processing system, 3) a data logger, monitoring root and aerial zone of the growing environment, 4) a dynamic database module for data storage and analysis, and 5) host computer overseeing all functions.

After placing the camera housing to designated locations, for image acquisition, panoramic canopy images were dynamically created from color, near infrared (NIR) and thermal cameras. The three layers were aligned such that the crop canopy now contains signature detection as a continuum. From the color layer, the plant canopy was extracted using a Hue-Saturation-Luminance (HSL) filtering. The filtering classified color pixels within the HSL range to be white and the pixels outside the range as black. This new layer was classified as the top projected canopy area (TPCA) layer. From this layer, the plant’s morphology was extracted. Similarly, this layer was used as a foreground mask for each of the three layers. This focused on the plant-only regions, extracting their respectful plant features. The extracted features were color (red-green-blue, hue-saturation-luminance, and color brightness), texture (entropy, energy, contrast, and homogeneity), Normalized Difference Vegetative Index (NDVI) (as well as other similar indices from the color and NIR channels), and thermal (plant and canopy temperature). The machine vision system identified regions within the image, based on a mosaic pattern, storing the extracted features focusing on each individual lettuce plant.

The conclusion of the manuscript was an example of the system’s capability, illustrating a one-day sample of the lettuce plants growing in the NFT channels. The
The project’s second objective, applied the constructed machine vision system to several experiments. The manuscript of the experiments, found in Appendix B, identified significant features used to classify the emergence of the applied plant water stress.

Two data sets, each containing three water stress cycles were applied at various times of a plant’s growth, during the approximately 3 week growth period. The first applied water stress occurred when the plants were small and not yet touching. The second applied water stress occurred when the plants started touching. The third water stress was applied when the plants formed a full canopy. An additional data set was also collected, examining only this third applied water stress at a lower light level condition.

All of the extracted features were also analyzed for temporal relationships to aid with the detection of cells that differed temporally. The created method evaluated a cell’s relationship toward the canopy by assessing the linearity of the canopy values. It was found that if a cell had a similar value to the canopy, that the linearity would be high. It was when cells differed from the canopy that the canopy’s linearity would reflect the deviation. By applying various threshold levels, the system could classify deviated cells from the canopy. While knowing the location of the control and treatment, the extracted features and temporal relationships from each of the water stress cycles were evaluated for sensitivity and statistical accuracy. It was based on the identified features from the statistical tests that led to the sensitivity threshold of less than 3.2% for false positive percentages and greater than 3.2% for true positive percentages. With this new classification for feature selection, at each water stress cycle, plant cell severity had been
ranked based on the number of features found within each cell. From the cell’s feature
count, a color coded graphical canopy image was generated to display the canopy health
and any possible emerging issues for the remote operator to evaluate.

3.2 Overall Conclusions and Recommendations

A multi sensor based machine vision platform was successfully designed and
developed capturing various plant canopy based features in real time. A multi variable
based plant water stress detection methodology, identification of plant stress locality and
presentation of color coded graphics for operator indicating stressed zone in the
production domain was established. Based on the collective results of this research, it was
found that the morphological feature, Top Projected Canopy Area, was found to be a
good marker for the initial growth period while the vegetation indices were more capable
at capturing the repeated stress occurrences during the various stages of the lettuce crop.
Lastly, the crop’s canopy temperature was shown to be a significant and dominant marker
to timely detect the water stress.

The results showed that the performance of the machine vision system was
affected by ambient light intensity and incidents of structural shadows on the canopy. The
stress detection methodology was not able to replicate the same feature detection for
similar stresses on the same plant. Attention must be paid to improve the image
acquisition or the elimination of these negative environmental effects. Therefore this
project was classified as successful at establishing a multi sensor and variable based crop
health and growth monitoring with specific example applications of water stress
detection, and a pioneering baseline comparable study for future multi-variable based
crop monitoring studies for CEA settings. Any improvement or modification to the
system’s design will generate results, evaluating for or against the results of this
dissertation. Establishing a baseline for a system is important by identifying a subjective
determination of what the acceptable performance is. For this project, a machine vision
system needs to reproduce meaningful patterns in data, especially when evaluating the
same plant with the same stress. Even though the system was able to collect meaningful
data and successfully represented the plant canopy for a remote grower, improvements
can still be made. Therefore, the following are some recommendations to improve the
system’s performance.

Great care was needed to be given when servicing the tri-camera housing. The
slightest nudge to the camera would cause the image to be out of alignment. An
improvement could be the actual housing and placement of the cameras, adding
accurately positioning platforms (adjusted by fine screws) for the camera’s to be mounted
on. This would maintain proper camera alignment with repeated accurate positioning
without the need for constant recreation of the automated alignment files. The positioning
platform could even theoretically adjust the camera in all orientations: X, Y, Z, yaw,
pitch, and roll. By increasing the accuracy of the camera alignment, an improved image
stitching could result and in turn, improve the image layer alignment. Improving the
image layer alignment would result in better image data extraction.
When extracting the plant foreground from the background, the method that was found to work best was to sum the previous canopy blob image to the current one. This eliminated any missing plant regions from the filtering process (due to the incident shadows). Unfortunately, this in turn does not track the proper diurnal plant movements, especially during the experimental trials where the plant’s wilting could cause the appearance of the plant to shrink. Time and effort was exhausted attempting to identify an improved approach, extracting the plant regions from the background. An improvement to the experimental setup could be to use a uniform background of known color or feature and to instead, subtract the background from the foreground. This could be a more practical approach especially if a treatment were to be a nutrient deficiency, where the plant’s color would alter due to the stress.

It was found that the method for identifying where amongst the canopy variances existed. The appearances of shadows were easily identified as being that variance. Adding an external light fixture with the camera housing could help to illuminate the plant foreground (as well as normalize the solar light intensity). Also, with the addition of an external light source, night time imaging could occur, allowing the plant monitoring to occur 24 hours a day. Alternatively, having the camera system functioning in a greenhouse with high diffused glazing would also ensure the removal of shadows. The normalization of light intensity could still be needed despite the glazing due to the fact that time is needed for the camera system to successfully acquire all images from the
domain. During that time, varying light conditions can cause the perception of different intensities by the camera.

Despite the limitations identified as areas of possible improvements, the system is more than capable for deployment into a growth chamber (such as in a LGH type of system) where artificial lighting is used for plant photosynthesis and growth. This constant light source would also create constant shadows which could be properly handled by the system. Likewise, the machine vision system extracted the identified plant features which can be used to determine the overall plant growth and health status, but is capable of analyzing a much larger range of parameters for other plant phenotyping applications (i.e. perimeter, centroid, diameter etc).
4. REFERENCES


APPENDIX A - DESIGN AND IMPLEMENTATION OF A
COMPUTER VISION GUIDED GREENHOUSE CROP
DIAGNOSTICS SYSTEM

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In Review: Transactions of ASABE

Abstract
An autonomous computer vision guided plant sensing and monitoring system was
designed and constructed to continuously monitor temporal, morphological, and spectral
features of lettuce crop growing in a Nutrient Film Technique (NFT) hydroponics system.
The system consisted of five main components including 1) a stepper motor–driven
camera positioning system, 2) an image acquisition and processing system, 3) a data
logger, monitoring root and aerial zone of the growing environment, 4) a dynamic
database module for data storage and analysis, and 5) host computer overseeing all
functions. Panoramic canopy images were dynamically created from a color, near
infrared (NIR) and thermal cameras. From these three images, the crop features were
layered such that a single extracted crop (or a crop canopy) would contain information
from each layer. The extracted features are color (red-green-blue, hue-saturation-
luminance, and color brightness), texture (entropy, energy, contrast, and homogeneity),
Normalized Difference Vegetative Index (NDVI) (as well as other similar indices from
the color and NIR channels), thermal (plant and canopy temperature), plant morphology
(top projected plant and canopy area), and temporal changes of all these variables. The
computer vision guided system extracted these plant features and stored them into a
database autonomously. This paper introduces the design and system components in
detail. The system’s capability is illustrated with a one-day sample of the lettuce plants
growing in the Nutrient Film Technique (NFT) system.

Keywords
Computer vision, crop monitoring, data acquisition, greenhouse, image.

INTRODUCTION
Understanding how plants interact with their surrounding environment is essential
for improved climate control strategies and management in greenhouse plant production
systems. Traditionally, environmental parameters in greenhouses such as air temperature,
humidity, and carbon dioxide concentrations are monitored and controlled by sampling at
a single location as being representative of average conditions in the greenhouse. Thus, the macroclimate is controlled. However, the microclimate at the plant and leaf boundary layer control the exchange processes. Furthermore, the microclimate is influenced not only by the macroclimate but also by the physical state of the plants. Therefore, the systems having the most direct effect on greenhouse microclimate can be superior in terms of resource use efficiency.

By monitoring plant’s responses under a given environmental condition, the data derived from crop monitoring can be used to compare crops over time and space, enhancing the information for greenhouse climate control. However, a crop monitoring system should be capable of recording data continuously, automatically, and non-invasively if it will be used in a commercial greenhouse setting, especially for real time monitoring, decision support, and control applications. Additionally, the system must be robust and integrated with greenhouse crop management practices (Helmer et al., 2005). The use of smart systems and technologies with mechanization, automation, and robotic applications can help improve the resource use efficiency and productivity in controlled environment agriculture (CEA) systems.

With the advancements in computers and sensors, micro-precision technology has been available for controlled environment plant production. The micro-precision technology does not always mean high engineering precision, rather it refers to an enabling technology to first identify what, how much, and when a resource is needed by the plants and then performs the action required to meet the identified quantitative and
qualitative needs as precisely as possible. Available micro-precision technologies include speaking plant approach, artificial intelligence, bio-robotics, and bio-mechatronics. Some of these techniques and technologies are invasive and require contact measurements. It can be feasible to implement computational intelligence (CI) techniques to predict the most important and widely used plant morphological parameters such as plant growth mode or fruit growth modes for adjusting the operation of a greenhouse production system. Or, a more complete system can be developed to characterize the plant growth modes including quantitative and qualitative morphological features such as color, shape of leaves, flowers and plant head currently used by greenhouse growers. This can help capture the onset of undesired growth modes (Fitz-Rodriguez and Giacomelli, 2009). Therefore, the applications of CI techniques and automation with CEA plant production through real-time plant sensing and monitoring, desirably with non-invasive and non-contact capabilities, are needed (Kacira et al., 2005).

Computer vision can be used to extract various information from a targeted object including morphological (size, shape, texture), spectral (color, temperature, moisture), and temporal data (growth rate, development, dynamic change of spectral and morphological states). Previous efforts of computer vision and sensing have been successful on determining plant status by monitoring a single leaf (Seginer et al., 1992; Meyer et al., 1992; Shimizu and Heins, 1995; Revillon et al., 1998), or a single plant (Hetzroni et al., 1994; Ling et al., 1996; Kurata and Yan, 1996; Murase et al., 1997; Kacira et al., 2002; Changying and Guanghui, 2003). However, monitoring and sampling
from the crop as a canopy would be more desirable (Leinonen and Jones, 2004; Ushada et al., 2007; Hendrawan and Murase, 2009).

For commercial production settings, it is more advantageous to develop a real-time plant canopy health, growth and quality monitoring system with multi-sensor platforms. This can be achieved simply by a sensing system equipped with a multi-sensor platform moving over the canopy and ultimately using plants as “sensors” to communicate their true status and needs. Such systems can be used to detect crop deviations from normal development and crop stress (i.e. nutrient deficiencies or diseases). Knowing the value-added benefits of the real-time plant monitoring systems, researchers have paved the way for the commercialization of robotic machine vision systems to be implemented within greenhouse/growth chamber settings. The HortiMaX (www.hortimax.com) CropView system allows the grower to capture images of their plant canopy 24 hours a day, 7 days a week and time-stamped the images to corresponding greenhouse climatic data/events. The grower can only view the plants, not extract plant or canopy features to quantitatively determine overall plant growth and status over time. In other words, if there’s a plant-related problem, the trend of this issue is not identified until the grower visually identifies the problem themselves, typically when it’s too late. Interest has been also increasing on high throughput phenotyping systems. More accurate phenotyping systems and strategies are necessary to enable high-resolution mapping and genome-wide association studies and genomic selection models in crop improvement effort. Thus, the goal of modern phenotyping must be to increase
precision, accuracy, and throughput of phenotypic estimations at all levels of biological organization. However, the costs and labor associated in the process must be minimized by automation, remote sensing, enhanced data integration and analysis (Cobb and DeClerck, 2013). LemnaTec (www.lemnatec.com) on the other hand, provides several Scanalyzer products, which monitors the plant as a continuum by automatically positioning the plant or camera to designated locations for controlled imagery and analysis. The level of accuracy from the Scanalyzer promotes the high precision required for plant phenotyping on a broad level. This system is mainly for lab and greenhouse phenotyping settings and may not be practical for plant production on a commercial scale. To combat this disadvantage, LemnaTec offers a larger model, Scanalyzer Field, which offers similar precision for field scale operations. The Scanalyzer Field acquires plant imagery in three-dimensions as well as associating the imagery with measured environmental conditions. This product does offer the complexity needed for the monitoring of plant production commercial operations except that there has been no literature on the system’s performance, or how the camera system was able to deal with the shadows and uncontrolled light conditions.

To restate, there has been increasing interest from research and commercial greenhouse operation settings for non-invasive and not contact real time crop monitoring and diagnostic systems. The changes in plant color, morphology, thermal features can be indicative of plant disease or stresses, therefore monitoring the crop and analyzing these features in real time and providing qualitative and quantitative information to the growers
can help them prevent damage to the crops, manage resources optimally, better monitor all aspects of the plant growth, and improve overall production quality. Therefore, this study was aimed at designing and implementing a computer vision guided plant monitoring system, which can be used in real-time crop diagnostics dealing with the uncertainty of environmental light characteristics using color, texture, crop indices, crop temperature, and temporal changes of the extracted features. This paper describes the system components, design, and implementation of the developed system.

**MATERIALS AND METHOD**

Growers have expressed an interest to see as much detail about their growing domain as possible. For plant imaging, this means the need to generate high resolution images, allowing the grower to see their plants in large detail. With a digital camera, sequential images, with an overlapping region of interest, can be stitched together to generate high resolution, panoramic images. A robotic positioning system can be used to place these digital cameras to designated locations, such that the acquired images can be automatically stitched. Once a panoramic image has been generated, the plant regions can be separated from the background for extracting significant features and their analysis. The designed and constructed plant monitoring system thus includes five main components: 1) a stepper motor–driven camera positioning system, 2) an image acquisition and processing system, 3) a data logger, monitoring root and aerial zone of the growing environment, 4) a dynamic database module for data storage and analysis,
and 5) a host computer overseeing all functions. Figure 1 illustrates the connectivity of the system components and Figure 2 identifies the flow diagram of the system developed for plant sensing and monitoring.

Figure 1. Computer vision guided crop diagnostics system components overview.
Figure 2. Overall signal processing flow diagram.

This study was developed in a research greenhouse at The University of Arizona, Controlled Environment Agriculture Center (Tucson, Arizona). A host computer was used for operational control of the plant monitoring system, stored in a custom built insulated cabinet whose internal environment (controlled by an air-conditioning unit) was specifically controlled for computer equipment (Figure 3). The climate controlled cabinet also housed the stepper motor drivers, a data logger (to monitor the plant’s root-zone and aerial environments), network-based external hard drive, and a network switch (to allow remote access to the computer and stored data).
The program for the plant health monitoring system was custom built, written with Microsoft’s Visual Studio 2010 in the VB.NET language. Some of the image processing tools were used from the AForge.NET library (www.aforgenet.com) and Emgu CV, a .NET wrapper for the OpenCV image processing library (www.emgu.com).
Robotic Camera Positioning System

The robotic camera positioning system consisted of three joined rails. Two parallel beams defined the y-axis coordinate (Figure 4b) and the third beam crossing perpendicular on top of the two y-axis beams formed the x-axis coordinate (Figure 4c). Together, these three beams in association with two more side beams built a 152.4x152.4 cm square frame allowing the camera platform to be positioned anywhere within this XY-coordinate system, above the crop canopy in the NFT system.

Two stepper motors (MD2-b, Arrick Robotics Inc., Tyler, TX) powered the robotic camera positioning platform in the XY-coordinate system (Figure 4d). Both motors were operated by a stepper motor driver (MD-2, Arrick Robotics, Tyler, TX) connected to the LPT printer port of a serial-based driver controller (C4, Arrick Robotics, Tyler, TX), which was in turn connected to the host computer via the USB/serial port. This computer sent movement commands to the C4 hub activating and monitoring the movement of the stepper motors. Once the movement command has finished, the C4 hub replied to the computer with a “movement finished” statement, identifying that the computer can execute the next task.
Figure 4. Complete NFT growing system setup within the greenhouse. a) Computer equipment cabinet, b) Y-Axis positioning rail, c) X-Axis positioning rail, d) Two stepper motors one for each the X and Y-Axis rails, e) Tri-camera housing, f) Aerial environment sensors, g) Nutrient solution chiller, h) Nutrient solution reservoir, i) Root-zone environment sensors, j) External irrigation pump.

Image Acquisition
Three digital GigE cameras (Tri-cameras) were used to generate the high quality images in the design and construction of this plant monitoring system: 1) color camera with a built-in NIR blocker (DFK 23G445, Imaging Source, Charlotte, NC), 2) grayscale camera (DMK 23G445, Imaging Source, Charlotte, NC) with NIR 850 nm bandpass-filter (67-853, Edmund Optics, Barrington, NJ), and 3) thermal camera (A325, FLIR, Wilsonville, OR). Each camera is powered with an external power supply adapter and communicated with the host computer through the network switch. The color and NIR cameras were equipped with a machine vision lens whose focal length is 8.50 mm and a field of view of 32.7° (NT58-000, Edmund Optics, Barrington, NJ). The color and NIR
cameras both generated an image of size 1280x960 pixels and each picture is saved as a jpeg with 95% quality, which was found to have an acceptable compression with nearly no loss of detail. The thermal camera generated a 2D array as size 320x240 of type-Single values. Because the thermal camera detects an objects thermal radiance (in the thermal range 7.5–13 µm), the resolution of detection is of 0.01 K for each 2D cell value. Each type-Single cell value is multiplied by 100 to convert the temperature value into an integer value which is then converted to a 3-Byte value array. The 3-byte arrays are split into individual bytes for each to be stored into an image’s R-G-B channel. The resulting image was saved as a lossless bitmap image, with the Portable Network Graphics format, which is not an actual image but instead, a place-holder for the larger image stitching to occur. After image stitching, the 3 bytes (from the R-G-B channels) are then converted back to a temperature value.

The tri-camera housing (Figure 5) was custom built from sheet metal. A cooling fan was attached at the base (top-side), where the camera housing is connected to the positioning system. This cooling fan serves as two purposes: 1) to move air past the cameras to ensure they don’t overheat and 2) to move dust down away from the camera lenses. The positioning of each camera was designed so that each camera lens is aligned at the same horizontal plane and height.
Panoramic Image Stitching

Due to the distortions the lens projects onto the imaging sensor, overlapping regions from images would appear to not be aligned (Figure 6a). The distortions can be calculated and removed from the image through image rectification, which improves the overall image alignment (Figure 6b). Image distortions are identified by taking several pictures of a checkerboard. The checkerboard has straight and parallel lines which, when mapped, are used to identify the image distortions.

After correcting for the lens distortions, the image alignment is identified by relating the sequential images by their overlapping regions (dark regions in Figure 6a and
6b). Because the XY positioning system consistently moves to the same locations for image acquisition, the overlapping regions are constant. The image displacements are recorded as a change in X and Y locations. The stitching function automatically recognizes these displacement locations and when preparing to execute the stitching, various optimization techniques can be used for a seamless panoramic appearance (Figure 6c). For this constructed system, no stitching optimization was used due to the need for constantly aligning the image, from one panoramic alignment to the next. In other words, the optimization may remove plant regions to ensure a better appearing stitch.
Figure 6. Stitching alignments showing dark regions in the middle identify good overlapping regions. 
a) Unrectified images, b) Rectified images, c) Stitched rectified images.

All image stitching was automatically done through command-prompt scripts from PanoTools (wiki.panotools.org) but the image rectification and alignment parameters were initially created through the desktop software, Hugin (hugin.sourceforge.net). With Hugin, camera parameter and movement project files were
created once and applied to each image collection run, dynamically creating panoramic images.

Figure 7 illustrates an example of the tri-camera stitched canopy images, layered so that the plant regions are aligned for feature analysis. The top-most layer is the resulting extracted plant blobs (discussed in section 2.4). The resulting images were 4340x3708 pixels and at 72 dpi, the resulting image would be approximately representing a region of interest (ROI) of 1.53x1.31 m in size.

![Figure 7. Stitched canopy images from the Tri-camera system, with the first top-most layer being the extracted plant blob layer.](image)

**Image Analysis and Feature Extraction**

Image segmentation, partitioning of an original image into various segments, is important for various image processing applications such as object identification and pattern recognition. Once the crop canopy’s panoramic color image has been stitched, it
is necessary to identify the plant-regions within the image. The extraction method that was performed was a Hue-Saturation-Luminance (H-S-L) filtering which actively selects the plant’s green color as foreground from the rest of the image as background, which was never green in color. This color filtering classified all green regions as a white color and everything else was identified as a black color. This binarization process was a simplistic approach to extract the plant foreground as white blobs:

$$\text{Blob} : P[i,j] = \begin{cases} 
1 & \text{if } \text{Color} : P[i,j] \in \text{Hue}(50:120) \\
0 & \text{else } \text{Sat}(0.1:1.0), \text{Lum}(0.0:0.6) 
\end{cases}$$  \hspace{1cm} (1)$$

Where, Blob: $P[i, j]$ is the designated monochromatic blob pixel (1 represents foreground, 0 represents background); Color: $P[i, j]$ is the designated color pixel located at $[i,j]$; Hue, Sat (Saturation), and Lum (Luminance) are each ranges that the color pixel is allowed to fall within to be considered as foreground.

With the image segmented into two regions, the image was further processed to remove small noises. To do this, a blob minimum-size analysis was performed, filtering out any unconnected blob that had a width and height size of 40x40 pixels or smaller. From this resulting monochromatic blob-image, the plant morphology feature, Top Projected Canopy Area (TPCA), is extracted by using the following formula:

$$\text{TPCA}: \sum_i \sum_j \text{Blob} : P[i,j]$$  \hspace{1cm} (2)$$

Where, Blob: $P[i, j]$ is the designated monochromatic blob pixel (1 represents foreground, 0 represents background).
This focused plant-blob image (top most layer in Figure 7) was overlaid on top of each of the three images, using the white blob region to extract the plant-only portion from the corresponding images. For the color layer, the plant-region was used to calculate the color-features of the plant canopy. All colored pixels were averaged together to identify the overall plant (or canopy) color. The averaged color value was stored into the database for analysis as Red-Green-Blue (RGB), Hue-Saturation-Luminance (HSL), and Color Brightness, which is a numerical representation of the color’s brightness to the human eye (Bezryadin et al., 2007).

A gray-level co-occurrence matrix was created by converting this color plant image to grayscale, capturing the spatial dependence of gray-level values contributing to the perception of the plant’s texture (Jain et al., 1995). Since the image texture is orientation dependent, four different matrices were calculated based on the different angles of pixel relativity (0°, 45°, 90°, and 135°). Each matrix was run through probability-density functions to determine textural parameters. In a review, twenty one different textural parameters have been studied to evaluate plant status (Zheng et al., 2006). Ushada et al. (2007) reported only four textural parameters; Energy, Entropy, Contrast and Homogeneity, were useful in identifying plant health for a moss plant.

After analyzing the color features of the focused plant image, the textural features were then extracted. These extracted canopy textural features were (Jain et al, 1995; Ushada et al, 2007):

Entropy: \[ \sum_i \sum_j P[i, j] \log P[i, j] \]
Energy:
\[ \sum_i \sum_j P^2[i, j] \]  
(4)

Contrast:
\[ \sum_i \sum_j (i - j)^2 P[i, j] \]  
(5)

Homogeneity:
\[ \sum_i \sum_j \frac{P[i, j]}{1 + |i - j|} \]  
(6)

Where, \( P[i, j] \) is the probability density function with gray levels located at \( i \) and \( j \).

The plant’s NIR reflectivity was also extracted when the plant-blob image was overlaid onto the NIR canopy image, averaged for the entire plant area and stored for analysis. A plant is highly reflective in the NIR band due to the internal cellular structure of a plant’s leaf (Penuelas and Filella, 1998). If a plant exhibits a stress, this internal leaf structure changes, resulting in a change of the NIR reflectivity. Analysis of this NIR value to the plant’s Red channel value has been shown to be a good indicator of plant health (Gamon et al., 1995; El-Shikha et al., 2007; Ryu et al., 2010). Two relationships for NIR to Red comparisons that were implemented, a reflectance ratio (SR – simple ratio) and the normalized difference vegetation index (NDVI). Relationships of the NIR value to other color values have also been evaluated (NIR-Green and NIR-Blue) as well as a unique relationship similar to the NDVI, the enhanced normalized difference vegetation index (ENDVI).

SR:
\[ \frac{\text{NIR}}{\text{Color}} \]  
(7)

NDVI:
\[ \frac{\text{NIR} - \text{Color}}{\text{NIR} + \text{Color}} \]  
(8)
ENDVI: \[
\frac{(NIR + \text{Green}) - (2 \times \text{Blue})}{(NIR + \text{Green}) + (2 \times \text{Blue})}
\text{ (9)}
\]

Where, \(NIR\) is the reflected NIR plant canopy value and \(\text{Color}\) is the reflected color plant canopy (Red, Green, or Blue channels).

Lastly, the plant-blob image is overlaid onto the thermal canopy image, extracting the plant’s average temperature to be stored and used for analysis. Analyzing a plant’s temperature or mainly, the plant’s temperature regulating mechanism (the stomata cells) through transpiration, we can identify the plant’s overall health (Hetherington 1998). When the stomata cells are open, carbon dioxide enters the plant while oxygen and water vapor leaves the plant. The exiting of the water vapor provides two internal functions: 1) the process cools the plant and 2) the process causes suction, drawing up more water and nutrients from the root system. When the plant is under stress, the function of the stomata cells reflects this stress and in turn alters the plant’s overall temperature. By comparing the plant temperature to a known well watered (un-stressed) plant temperature and a non-watered (stressed) plant temperature, a water-stress index (CWSI) or the overall stomatal conductance \((I_G)\) can be inferred (Jones, 1999; Jones et al., 2002; Cohen et al., 2005).

CWSI:
\[
\frac{T_{\text{canopy}} - T_{\text{wet}}}{T_{\text{dry}} - T_{\text{wet}}}
\text{ (9)}
\]

\(I_G:\)
\[
\frac{T_{\text{dry}} - T_{\text{canopy}}}{T_{\text{canopy}} - T_{\text{wet}}}
\text{ (10)}
\]

Where, \(T_{\text{canopy}}\) is the extracted canopy temperature, \(T_{\text{wet}}\) is the measured well-watered plant temperature, and \(T_{\text{dry}}\) is the measured non-watered plant temperature.
In a large scale, automated camera system, it is not practical to closely monitor indicator plants to maintain the wet/dry temperature difference. Therefore, instead of monitoring a wet-leaf and dry-leaf temperature, theoretical values can be calculated by knowing the aerial environment of the plants (Jones, 1999; Jones et al., 2002). This CWSI calculation was not performed in the current study, but the key variables in performing the calculation have been made available to offer the ability to add this feature in the future.

The developed crop monitoring system enabled monitoring and collection of a total of seventeen variables, as potential features to be analyzed and used for crop monitoring and diagnostics.

**RESULTS AND DISCUSSION**

**Positioning System’s Movement and System Maintenance**

It was found that the best movement pattern to execute was a zigzag pattern, making seven stops both in the X and Y direction. This movement pattern resulted with a total of 49 acquired images from one camera. This pattern allowed a decent overlap of acquired images for image stitching and had an acceptable travel time of 6 minutes and 28 seconds, moving over the entire growing domain. A specific movement speed was selected to ensure the motion stability of the camera platform. By increasing this speed, the total traveling time could have been improved but in the long run, might affect this motion stability. Also, any increase of stops can lengthen the travel time but not improve
the quality of the image stitching. Likewise, any decrease in stops can improve the movement time but decrease the stitching ability.

Bi-weekly maintenance was performed on the positioning system to minimize the negative effects of dust, heat, and air moisture on the system. Bearings and cable straighteners were lubricated for proper motion of the system. Any loose screws on gears and pulley’s was regularly checked and corrected as part of the maintenance activity. The tri-camera system did not require frequent servicing. However, if interaction with the cameras was needed, care was given to not accidentally nudge the cameras resulting in the need for image realignment. An approach to improve this is to allow the ability to accurately position the cameras inside the camera housing by fine tuning the cameras to specific locations, preserving the original alignment configurations.

**Image Processing and Feature Extraction**

After the camera system acquired the targeted 49 images, the host computer then stitched the images together to generate a large panoramic image. It took the system approximately 3.5 minutes to completely stitch all three of the tri-camera images. Once completed, the system then focused on generating the plant-blob image from the completed color layer image. Through blob extraction and noise removal, the system took approximately 28 seconds to generate the plant-blob image. With all four image layers created, the system now extracted the plant features from each layer to be stored within the database for analysis. This data extraction step took the system approximately 47
seconds to complete. From the start of image acquisition to the end of the data extraction, the entire process took the host computer approximately 11.2 minutes to complete.

With plant image analysis, it is always necessary to segment the plant image into two regions, the focused plant as the foreground and everything else as the background. To easily identify the plant foreground, a uniform background of known color is implemented. Actively selecting this color as the background easily enables the ability to label the plant regions as the foreground (Seginer et al., 1992; Hetzroni et al., 1994; Kacira et al., 2002). When the background is unknown, researchers have developed strategies to focus on the plant region by subtracting the background from the image (Meyer and Neto, 2008; Guijarro et al., 2011). After the background has been removed, the image then needs a threshold to be applied such that the background and foreground regions can be appropriately labeled. The most popular method for performing plant foreground/background image thresholding is Otsu’s thresholding method (Otsu, 1979). This method assumes that the image is composed of two classes - a foreground and a background. Through statistical analysis of the image’s weighted histogram, the threshold is identified to be the point where the smallest variances within these two classes exist. This approach has advantages as being an easy and fast speed method. However, as the plants grow, forming a full canopy, the method starts looking at identifying two classes within the full canopy, resulting in noisy images (Figure 8, middle column). The segmentation method implemented in this study, actively selects the green-plant color which proved to be more accurate at selecting the plant region despite their growth size.
(Figure 8, right column). A drawback though is to ensure the background does not contain the targeted foreground color and that the focused plant regions are of a similar color.

![Figure 8. Plant blob extraction examples. The left column is the original images, the top being seedlings, bottom being the full plant canopy. The center column is the plant extraction from the background based on the enhanced plant region with Otsu threshold method. The right column is the plant extraction from the background based on the HSL filtering.]

One of the major challenges faced, is that shadows and inconsistent light conditions affected information contained in the images (i.e. with the color plant image or plant NIR reflectivity). These environmental noises have even caused discrepancies with the plant blob extraction (Figure 9a). In this study, we used a summation of previous plant blob images to automatically and continually identify plant regions. Whether a plant was detected or not, this summation ensured the plant region maintained the same
location, allowing the environmental inconsistencies to be ignored from the plant extraction (Figure 9b). This approach doesn’t take into consideration that a plant may shrink slightly during its diurnal movements. Since, this plant blob variance was significantly smaller than the overall plant size (Figure 9b), it was therefore ignored in this study. But, if an unexpected adjustment to the NFT system occurs, while the imaging is running, then the overlaid plant canopy blob will have a large deviation and re-creation of this plant blob layer will be needed in order to properly extract the plant features.

![Plant blob extraction method for handling unfavorable environmental conditions.](image)

**Figure 9.** Plant blob extraction method for handling unfavorable environmental conditions. a) The original blob extraction overlaid onto the color image, b) The improved plant blob overlaid onto the same color image giving an improved plant canopy extraction. Also to note, the plant blob is slightly larger than the actual plant, c) A focused plant where the lighting conditions emphasize the plant’s texture altering the perception of the plant at that specific moment of time.

In addition to the environmental inconsistencies affecting the plant-blob extraction, these inconsistencies were also reflected in the extracted features (Figure 9b
and 9c). Feature normalization or adjustment (i.e. shadow removal) based on the environmental conditions can be used to improve the feature’s quality. In this study, frequent data collection and a moving-hourly average was used to cancel the environmental effects on the extracted features. An example of three extracted features (Figure 10) is shown, among the seventeen total analyzed by the developed system, with its corresponding moving-hourly average.

Figure 10. Examples of the extracted plant features. The blue points represent the average of 120 plants at that specific time whereas the red points are a moving average of 6 points.
Potential Research Application with the Plant Monitoring System

An example of a potential research application with the developed system is provided in this section by illustrating its capability to monitor an NFT growing domain of 10 rows, each row with 12 lettuce plants, spaced approximately 15.2 cm apart (Figure 4). The system started daily at 7am and ended at 6pm, acquiring canopy images every 10 minutes. Figure 10 identifies the system’s capability of extracting the canopy’s morphological (TPCA) and spectral (NDVI and canopy temperature in the IR region) features of greenhouse grown lettuce crop over a one day period. Each data point is shown as an average of the 120 plants.

If a treatment were to be applied, this system can monitor the health and growth features temporally, identifying statistically significant changes between the control and treatment groups. A methodology is required to accurately and timely determine the onset of stress or growth deviated from normal. This effort is current underway as an additional part of this study.

CONCLUSION

A machine vision guided plant sensing and monitoring system was constructed to continuously monitor: color, morphological, textural, and spectral (crop indices and temperature) features from a crop canopy. The developed system used a distributed processing hierarchy with motion control, image acquisition, and environmental data collection. Sources of reduced image quality and plant extraction accuracy were analyzed
and quantified. Measures were taken to improve each source of inaccuracy. The developed system can autonomously monitor and extract Red-Green-Blue, Hue-Saturation-Luminance, color brightness as color features; entropy, energy, contrast, and homogeneity as textural features; TPCA as a morphological feature; NIR reflectivity, and thermal radiation from a single plant or a plant canopy. Thus, a total of seventeen features are temporally collected and provided for the operator by the system. The machine vision system extracted these identified plant features which can be used to determine the overall plant growth and health status, but is capable of analyzing a much larger range of parameters for other plant phenotyping applications (i.e. perimeter, centroid, diameter etc). The system is an adaptable sensing and monitoring platform which can collect greenhouse aerial, non-contact crop related, and crop root zone data enabling to establish the monitoring of a plant’s environment as a seamless continuum. This can certainly help analyzing crop and microclimate interactions more closely and can lead to improved greenhouse and crop resource use management practices. Combining the systems capability with a decision support system can assist in dealing with identifying complexity of the crop stress symptoms and an increased control of the overall plant growth environment, which can potentially improve resource use efficiency in controlled environment crop production systems.
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REFERENCES


APPENDIX B - MACHINE VISION GUIDED MULTI-VARIABLE
BASED CROP DIAGNOSTICS IN GREENHOUSE

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Abstract
A methodology from a multi-camera based machine vision system, located within a greenhouse, was developed and evaluated to timely identify crop water stress. The developed methodology consisted of multiple variables designed to determine the locality of the emerging water stress with lettuce plants, dealing with the uncertainty of light intensities and incidents of shadows amongst the plant canopy. Features extracted from the various cameras were quantified for sensitivity and classified statistically to identify the treatment from the control. The accumulation of selected features per plant was converted to a color scale indicating plant severity, displaying the overall canopy health for the remote operator. The feature analysis showed that the morphological feature, Top Projected Canopy Area, was found to be a good marker for the initial growth period while the Enhanced Normalized Difference Vegetation Index and Normalized Difference Vegetation Index (NIR to Red and NIR to Blue) were more capable at capturing the repeated stress occurrences during the various stages of the lettuce crop. Furthermore, the crop’s canopy temperature was shown to be a significant and dominant marker to timely detect the water stress occurrences. The study established a unique multi-variable machine vision based crop diagnostic system and methodology for use in controlled environment agriculture settings.

Keywords
Machine vision, water stress, crop diagnostics, crop monitoring, greenhouse.

INTRODUCTION
High precision agriculture has become a popular concept, growing higher quality produce and improved yields through minimizing resource usage (McBratney et al., 2005). An important resource that all plants need and has become an increased topic of minimizing is water usage (Hsiao et al., 2007). A healthy plant absorbs water and releases the water vapor through the stomata cells by transpiration. This process enables plants to intake carbon dioxide while releasing water vapor and oxygen into the
atmosphere. Applying the proper dosage of water to the plant not only ensures the conservation of water but also can promote secondary metabolic characteristics that are desirable for pharmaceutical/nutraceutical applications (Khalid 2006).

Some precision techniques of water management within controlled environment agriculture involve measurement of the aerial environment (Katsoulas et al., 2002; Boulard and Baille, 1993; Idso, 1982) or root-zone environment (Kirda et al., 2004) leading to the knowledge of the macro-environmental demands upon the plant. With these measurements there is an improved control of the water usage, but the plant leaf-boundary layer has more effect on the actual water demand for the plants. Through plant contact-sensing, researchers have studied the plant’s micro-environment for water stress detection (Liu et al., 2007; Takagi et al., 1998; Baille et al., 1994). The level of precision has greatly increased but contact sensing is cumbersome, often destructive, and in commercial settings, is difficult to identify overall canopy demands from single representative plants. As a result, researchers have focused on plant water stress detection through non-contact sensing techniques.

As a plant goes through the stress from the lack of water, the stomata cells will close to preserve the water content within the leaf. This in turn prevents the plant’s transpiration, maintaining a proper leaf temperature (Hetherington 1998). González-Dugo et al. (2006) has shown that the variability of plant canopy temperature was a useful factor with identifying the emergence of water stress, correlating their findings to the well established Crop Water Stress Index (CWSI). Ushada et al. (2007) has shown that as a
plant wilts, their textural features reflect these changes. Similarly, the plant’s morphology also changes due to the low internal turgor pressure (Foucher et al., 2004). Kim et al. (2011) used a hyperspectral camera and separate normalized difference vegetation index (NDVI) detectors to identify the total reflectivity of the plant water stress with apple trees. Their study concludes that high water stress correlation was found at the narrowband red-edge NDVI (705 and 750 nm) and the broadband NDVI (680 and 800 nm).

Identification of causes for stress is difficult and challenging since plant stress can be a combined factor of water, nutrient, and pest infestation. Remote and non-contact sensing technology can provide an improved and more practical plant stress assessment especially for real-time monitoring and control of greenhouse crop production system. Furthermore, a multi-sensor based machine vision system for crop diagnostics can improve stress sensing capability by monitoring and analyzing important spectral features from crop canopy in longer and wider range of wavelengths that are beyond a visible range.

There has been increasing interest from greenhouse climate control system manufacturers and greenhouse plant growers towards the inclusion of real-time crop monitoring and diagnostic systems to help with the decision making process of ensuring a greenhouse’s environment is maintained for maximum plant growth. The existing commercially available crop monitoring systems with image capture capability only provides access to the image database or crop production zone with webcam uses,
without processing the collected images, indicating growth or health status of the crop canopy. Additionally, to our knowledge, given a 2-dimensional plant domain region, the autonomous detection of an emerging plant stress based on multi-variables from multiple cameras are not identified from any of the methodologies presented in the literature. Therefore, the objectives of this study include: 1) evaluating a custom built multi-sensor based machine vision system’s capability and identifying significant features separating the control and treatment from an induced water stress experiment, and 2) identifying, amongst the plant canopy, the location of the emerging water stress timely by using the found significant features.

**MATERIALS AND METHOD**

This project was conducted in a research greenhouse at Controlled Environment Agriculture Center at The University of Arizona, Tucson, Arizona. The set point for the day/night greenhouse air temperatures were 22°C and 18°C respectively. The water stress treatment was applied by withholding nutrient solution from a selection of Nutrient Film Technique (NFT) rows consistently at 9am. This was done by plugging the input irrigation line of the treatment channels. Once human vision detected symptoms of the water stress, the flow of nutrient solution was allowed back to the channels, enabling the plants to recover from the water stress. This water stress cycle occurred three times during the growth of the plants. The first treatment initiated when the seedlings were small and non-touching (Figure 1a). The second treatment was applied when the
seedlings were slightly larger and started to touch neighboring plants (Figure 1b). The last treatment was executed when a full canopy was formed, approximately a week before harvesting (Figure 1c). Two experimental data sets were obtained of these three water stress cycles, and a third experimental data set was obtained with only the third water stress cycle, at the mature stage of the plant.

![Figure 1. Three stages of plant growth where the water stress was applied. a) Seedling to early growth stage; b) Early growth to full growth stage; c) Fully grown to harvest stage.](image)

**Plant Growth System**

Lettuce plants (Lactuca sativa cv. Rex) were initially grown in 2.5 cm rockwool seedling starter cubes for three weeks before being transplanted into the plant growth system. The system was built from ten, 1.8 m NFT channels (GroClean, American Hydroponics, Arcata, California) and arranged such that each channel was 15.2 cm apart. Each channel was drilled with twelve, 2 cm holes spaced by 15.2 cm aligning the lettuce plants to be at the center of each channel, allowing a total of 120 plants to grow. One end of the channel was capped off and inserted with an irrigation line, while the other end was slightly lipped to allow the nutrient solution to drain into a collection gutter. Each channel was angled by 2°, down towards the collection gutter so that the nutrient solution
will flow from one end towards the other. The collection gutter then drained to the nutrient solution reservoir where an external pump pushed the nutrient solution back into the channels. This recirculation continued 24 hours a day, 7 days a week (Figure 2).

Figure 2. Complete NFT growing system setup within the greenhouse. a) Climate controlled computer and data acquisition system equipment cabinet; b) XY-positioning rail; c) Tri-camera housing; d) Aerial environment sensors; e) Nutrient solution reservoir; f) External irrigation pump; g) Root-zone environment sensors.

The nutrient solution used was a Hoagland’s plant nutrient recipe maintaining a pH of 6.0 and an EC of about 1.8 dS m⁻¹. The root-zone pH/EC conditions were measured through pH and EC probes with transmitter (HI 98143, Hanna, Smithfield, Rhode Island). The root-zone temperature was measured with a Type-T thermocouple (Omega, Stamford, Connecticut) and maintained at 22°C with an external coil water chiller (Prime Drop-In Chiller, Current USA, Vista, California). Measurements of the plant’s aerial environment included incoming shortwave solar radiation with a pyranometer (SP-110, Apogee Instruments, Logan, Utah), air temperature/relative
humidity (HMP50, Vaisala, Helsinki, Finland), and CO2 concentration (GMT220, Vaisala, Helsinki, Finland). All environmental data was collected through a data logger (CR3000, Campbell Scientific, Logan, Utah), collecting data every 5 seconds and storing sensor averages every 10 minutes. All environmental data was stored into database tables with corresponding machine vision imagery data.

**Machine Vision System and Data Storage**

The reader is referred to Story and Kacira (2013) for the detailed information on the design and development of the machine vision system as well as the key image processing procedures for thresholding, image segmentation, blob analysis, and feature extraction which were used in the current study.

The automated machine vision system consisted of three digital GigE cameras attached to an X-Y positioning system, targeting the lettuce plants growing beneath. The positioning system placed the cameras to designated locations to acquire images. Because the camera was placed consistently at the same location, the relationship of one image to its neighbors is also known and constant. This known relationship was used in the automation of stitching the images together to form panoramic images of size 4340 x 4017 pixels. Each of the cameras would generate these panoramic images to create a multi-layer image of the plant domain. The three layers were color, near infra-red (NIR), and thermal (Figure 3 a, b, and c respectively).
From the color layer, the plant only blob image (Figure 3d) was created by extracting the plant foreground through a Hue-Saturation-Luminance filtering. The extracted plant regions in the image were colored white, while everything else was considered the background and colored black. Since shadows and inconsistent lighting has caused this extraction method to lose some plant regions, the previous blob image was summed to the current blob image to prevent this. Often, a slight background halo would be visible surrounding the plants during the diurnal movements, but the effect was considered negligible.

The use of the extracted plant blob image as a mask enabled the plant-only regions to be identified from the three image layers. The custom built automation software split the images into corresponding rows and columns. Twelve rows of height
309 pixels and fourteen columns of width 310 pixels resulted in the formation of 168 cells from a single acquired original image. The cell size was chosen so that the cells fall onto individual plants. From each of these image cells, various plant characteristics were calculated and stored for analysis. These features were plant morphology (top projected plant and canopy area), color features (red-green-blue, hue-saturation-luminance, and color brightness), textural features (entropy, energy, contrast, and homogeneity), normalized difference vegetative index (NDVI), enhanced difference vegetative index (ENDVI), and thermal features (plant and canopy temperature). The extracted data was then stored into a database for later retrieval and analysis.

The machine vision system’s control and data acquisition was done by custom built software written with Microsoft’s Visual Studio 2010 in the VB.NET language. It was far quicker to process unmanaged images, directly accessing image pixel locations and channels. In those instances managed to unmanaged bitmap object conversions was done through the EmguCV library (www.emgu.com). Additionally, plant blob extraction and image cleanup as well as evaluating plant images within varying color spaces was done through the AForge.NET library (www.aforgenet.com).

**Temporal Feature Derivation**

In addition to the extracted features from the plant imagery, temporal trend relationships were also calculated. The analysis evaluates the plant cell’s value to previously stored values, aiding in the classification of the cell’s plant health and growth status. These relationships are used to identify ratios or changes from the daily first value.
and the previous value, all based on a cell’s moving 1 hour average value. The six feature relationships are: 1) the cell’s average feature value, 2) a ratio of the current cell feature value to the cell’s first feature value of the day, 3) a ratio of the current cell feature value to the cell's previous feature value, 4) the cell’s variation from the first value of the day, 5) the cell’s variation between the current feature value to the previous feature value, and 6) the cell's feature value's coefficient of variation, indicating the variation relative to cell’s mean value.

Relationship1: 
\[ \text{Cell} \mu = \text{Cell} \mu \] (1)

Relationship2: 
\[ \frac{\text{Cell} \mu_i}{\text{Cell} \mu_0} \] (2)

Relationship3: 
\[ \frac{\text{Cell} \mu_i}{\text{Cell} \mu_{i-1}} \] (3)

Relationship4: 
\[ \text{Cell} \mu_i - \text{Cell} \mu_0 \] (4)

Relationship5: 
\[ \text{Cell} \mu_i - \text{Cell} \mu_{i-1} \] (5)

Relationship6: 
\[ (\text{Coefficient of Variation}) = \frac{\text{Cell} \sigma}{\text{Cell} \mu} \] (6)

Where \( \text{Cell} \mu \) represents the moving hourly average of the extracted cell feature and \( \text{Cell} \sigma \) is likewise the feature’s standard deviation. Subscript 0, denotes the first value of the day, subscript i, denotes the current value at a given date-time stamp, and subscript i-1, denotes the previous cell value from the given date-time stamp.
Identification of Plant Stress Locality

The guard rows from the plant domain have been ignored from all analysis in this study. The guard rows are classified as plants within the first and last NFT rows as well as the first and last columns within the growing domain (Figure 4). Before a statistical test could be applied, tests of Normality need to be verified to ensure the control and treatment’s mean and standard deviation are normally distributed. The Kolmogorov-Smirnov normality test (Conover, 1971) was applied which evaluates the sample data to a referenced normal distribution and under the null hypothesis, the statistic determines if the sample is pulled from the same distribution. After ensuring the extracted features are considered normal, statistical tests evaluating the significance between the control and treatment was applied.

Figure 4. The plant domain image identifying the location of the control, treatment, and guard rows.
To identify the location of the water stress, each cell’s value is compared to the entire canopy domain. If cells had a similar relationship to the domain then the cells value should also be similar. By charting the values of the domain, the similarity is seen as a highly correlated linear relationship (Figure 5 - blue line). When cell values differ from the domain, the variance influences the sample’s linearity (Figure 5 – red line). The linearity test performed was the Pearson’s R test which calculates a bivariate relationship. When the result of this test is squared, a linearity relationship can be evaluated into two groups. A resulting value close to one signifies a highly correlated linear relationship while a value close to zero means the relationship is un-correlated. When comparing the value’s domain $R^2$ test result to a threshold, cells are selected as being different if their value is outside the sample’s mean plus/minus two standard deviations ($\mu \pm 2\sigma$). Re-evaluating the sample’s $R^2$ and cell classification continues until the resulting domain sample is greater-than or equal to the $R^2$ threshold. A limit has been imposed on how often this loop occurs to ensure the program does not get caught in an infinite loop. Nine $R^2$ thresholds were used between 0.87 and 0.95 with 0.01 increments.
In order to identify if an extracted feature and temporal feature relationship was significant with identifying plant water stress, a statistical test with the knowledge of the control and treatment was needed. At each 10 minute data interval, the control and treatment are statistically evaluated with the Student’s t-test, at a 95% confidence. Figure 6 illustrates this procedure for hue feature as an example. A larger resulting significance value indicated the difference between the control and treatment. The significance test evaluated the difference between the control and treatment for a two day period, for instance ‘the day before’ a treatment was applied and ‘the day of’ the applied treatment. This evaluation occurred for each of the three water stress treatments and for all experiment sets.
Figure 6. Statistical comparison of the control and treatment showing the level of significant difference.

When the water stress treatment was applied, it was known that the plants would not exhibit the water stress symptoms immediately due to some water availability for the roots remaining in the rockwool cubes. When classifying features and temporal relationships, various treatment plants will exhibit the stress at various times (i.e. as a function of growth stage, demand conditions for transpiration, availability of water in the rootzone). Therefore, the baseline time chosen to classify the separation between control and treatment was at the time the water stress was applied. Any significance between the two groups detected before the time of the applied stress was considered a false positive and quantified into a false detection percentage rate. Any successful treatment detection after the time of the applied stress was classified as a true positive and quantified into a true detection percentage rate. The percentage rate was defined as the ratio of the count of the number of cells detected divided by the total number of possible cells to be detected.
These percentage rates helped compare the feature and temporal relationship’s sensitivity with identifying the control and treatment.

By using the true/false significance test as an initial detector, features found to have zero false positives and more than one hour worth of true positives were selected. Data is acquired every 10 minutes providing six data points for one hour period. Therefore, seven true positives were used as the minimum indicator to identify features that have been marked as significant for more than one hour of data. The importance relies on identifying strong features that show a clear difference between the control and treatment. From the significant features list, the average true/false positive detection percentage is calculated to be used as a threshold against all collected detection percentages. This now expands the features used to identify higher true positives with a low false positive detection rate. This new list of selected features was used to graphically show the emerging stress.

All cells flagged as being different from the canopy, using the specific features from the newly created list, were summed to identify the number of total features that a particular cell held. From this canopy summation array, a curve similar to the Receiver Operating Characteristic (ROC) curve was generated from knowing which cells were classified as the control and treatment (Zweig and Campbell, 1993). The ROC curve helps to identify the severity count, of both control and treatment, at varying specificity levels. The ROC graph, being a part of a decision support system, can enable the user to
select the specificity level that best emphasizes the treatment severity from the control severity and in turn, the system generates the resulting canopy output image.

In this study, three specificity levels (100, 67, and 50%) related to the number of features was used. A 100% level indicated that all feature counts meant a severe cell. A 67% level indicated that two-thirds of the total feature count, and 50% level indicated that half of the total feature counts meant that the cell was classified as severe. The severity does not indicate water-stress severity, but instead the specificity of features counted amongst the cell.

To display this graphically for the end user, the severity was color-coded such that no detected features represent a green color. Once the cell feature count was found greater than or equal to a specificity level, the cell was colored red, indicating the cell is flagged as being of concern. The Hue color space was used to classify this severity color gradient where green was the Hue value 120 and red was the Hue value 0. Based on the specificity level, the hue range of 120 to 0 was split accordingly such that each feature was incremented by a color level between green and red. Figure 7 is an example of this graphical user display for the canopy’s resulting data at the three specificity levels.
Figure 7. Example of three specificity levels based on an example of 6 selected features. a) Denotes the number of features detected within each cell; b) 100%; c) 67%; d) 50% of all identified features to specify the severity level.

To ensure the real-time functionality of the system, the data analysis was done by custom built software written with Microsoft’s Visual Studio 2010 in the VB.NET language. The statistical analysis (Kolmogorov-Smirnov test, Pearson’s R test, and the Student’s t-test) was done through the inclusion of .NET libraries from Meta Numerics (www.meta-numerics.net).

RESULTS AND DISCUSSION

Data collection started as soon as the seedlings were moved into the NFT production system and continued until the lettuce was ready for harvest, approximately
three weeks after transplanting. From seed to harvest, the entire growth period for both experiments was about six weeks.

The three experimental data sets conducted during this study had the day/night greenhouse air temperatures of $21.7/16.5 \pm 1.8/2.8^\circ C$, $23.0/20.1 \pm 2.5/2.8^\circ C$ and $20.2/13.4 \pm 1.3/1.6^\circ C$ as well as an average measured light intensity (in the greenhouse) of $160.4 \text{ W m}^{-2}$, $191.3 \text{ W m}^{-2}$, and $128.2 \text{ W m}^{-2}$ for the 1$^{\text{st}}$, 2$^{\text{nd}}$, and 3$^{\text{rd}}$ experimental data sets respectively. These varying light intensity levels helped evaluate the effect of inconsistent lighting on the performance of the stress diagnostics approach proposed in the study. The experimental setup was aimed at imitating a real world greenhouse setting and therefore no interaction occurred with the system’s exposure to light.

As the NFT channel’s irrigation line was plugged, the root/rockwool (that the plants were initially grown from) was still wet or maintained some water for the plant. A sign of water stress occurred after this initial dampness has dissipated. Depending on the plant’s growth stage, the onset of the water stress was found to be slower when the plants were at the seedling stage compared to a faster onset, when the plants were at the canopy closure stage. Earlier signs of the water stress were also noticed on days with higher irradiance.
The study showed that the plant temperature was a significant feature with timely identifying the onset of the water stress. The results based on thermal image and feature extraction showed that it was possible to detect water stress as early as two hours after the
start of the stress treatment (Figure 8). As seen from the extracted control/treatment thermal data (Figure 9), the three water stress treatments are clearly visible as higher temperatures than the control plants. There are three vertical lines for each of the water stresses denoting when the stress was applied on treatment group plants, when human visual detection was made, and when the water was returned to the treatment channels. It is interesting to note that after the second water stress cycle, even after the treatment was conducted, the treatment lettuce plants struggled to maintain lower temperatures in the subsequent days. This suggests that the plants internal cellular structure was damaged in this experimental set, needing several days to recover from the applied stress. Eventually, the treatment plants reached the temperature of those in the control group before applying the final water stress treatment.

Figure 9. Plant canopy temperature from the first experimental set showing the control/treatment. The three vertical lines represent experimental events: 1) Start of the water stress; 2) When human visual detection was made; 3) when water was reapplied for each of the water stress cycles.
With the plant temperature feature being quickly and strongly pronounced as a clear indicator of the emerging water stress, higher weight can be given to this feature for stress detection. But, for cases where the stress is not water-related, it is important to identify the strength of the other potential plant based markers.

Figure 10 is a side-by-side comparison of a typical control and treatment plant. We can see from the series of images that the plant looks to be of similar size. The machine vision accurately detects that one plant is approximately 700 pixels bigger. This is seen from the top projected canopy area (TCPA) graph, Figure 10a. This variation in the feature value is an example for the need to analyze temporal relationships (Figure 10b). Each of the graphs has vertical lines to denote when the treatment was applied and when human visual detection was made. Depending on the size of the lettuce plant at the time of the water stress, the plant will wilt, falling upon the NFT channel with the reduced turgor (as seen in this case). In this instance, the TPCA will show the plant to be constant. If the lettuce is larger than the channel, the plant will collapse between the channels giving a detection of a smaller (shrinking) TPCA value. Because of the current plant blob extraction method, the value was actually perceived as a constant (non-growing) value. Depending on the severity of the water stress, the plant’s internal cellular structure could be damaged. This has been perceived as a darkening of the lettuce color.

Figure 10c shows the plant reflectivity for the blue spectrum as an increase as the plant is exhibiting the stress. Similarly, Figure 10d shows this color alteration in the Hue spectrum. The internal cellular structure of a healthy plant is highly reflective in the NIR
band (Penuelas and Filella, 1998). With the water stress causing internal damage, this also resulted in a change of the NIR reflectivity (Figure 10e). The vegetation index relationships would also exhibit these variations (Figure 10f).
Figure 10. Top rows represent a cell image of a typical control and treatment during the process of the applied water stress. a) TPCA showing that the two plants are not equal; b) TPCA relationship showing similarity with stress affecting the change; c) Blue reflectivity; d) Hue Color; e) NIR reflectivity; f) ENDVI.
When evaluating control/treatment trends amongst the canopy (Figure 11), any discernible difference was lost. This was due to varying times of the treatment plants showing signs of the stress as well as the varying plant growth rates and environmental factors. Evaluating the values of the entire canopy, as per image cell basis, was proven not effective. This supports the need for a methodology to evaluate the canopy in its entirety.

![Figure 11. Hue Feature collection from the entire canopy.](image)

The recovery of the stress can still exhibit variances amongst the canopy. This supports the need to evaluate temporal changes or normalized features, using the first collected daily value as well as the previous value to reset the feature. If the plants are growing similar in a healthy fashion, these feature relationships would likewise exhibit similarly.
**Extracted Features**

There were seventeen features extracted from one image cell. Each of these seventeen features was evaluated by the six different temporal relationships at nine different $R^2$ threshold levels. Thus, a total of 918 features were analyzed for its ability to identify the difference between the control and treatment groups. Figure 12a shows only the results of the first data set’s first water stress analysis. This similar analysis occurred for each of the collected experimental data sets.
Figure 12. Graphical display of all classified extracted features. a) True/False Positive percentage relationship; b) Statistical list of features sorted by False Positive percentage, average is 3.2%; c) A close up of the desired region of True/False Positive features (the pink region).
Table 1 summarizes the number of significant features for the three experiments at each water stress treatment, again selecting only features with statistically significant treatment from control detections. With the identified selection criteria mentioned in section 2.4, the second experiment was found to have an extremely low significant feature count list. Figure 13 identifies that the overall experimental data set relative to the limiting criteria of zero false positives. This experimental data set performs poorly statistically, returning a low number of significant features despite analyzing varying true positive criteria. Because of this, the percentage calculation threshold was based on the significant features from the first experiment. Again, this calculation was only a means to identify which features from the 918 total collected features are sensitive to the treatment detection.

Figure 13. Second experimental data set showing the number of statistically significant features less than the desired limit.
Table 1. Number of significant features detected and the number of features found to meet the percentage criteria for each experimental run and water stress treatment.

<table>
<thead>
<tr>
<th>Experiments</th>
<th>1st water stress Feature Counts</th>
<th>2nd water stress Feature Counts</th>
<th>3rd water stress Feature Counts</th>
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<td>- -</td>
<td>- -</td>
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True/false detection percentages were calculated for each of the significant features from the first experiment and were grouped together, creating a list of 104 features (Figure 12b). The false positive percentages ranged from 0% to 20.7% with an average of 3.2%. This average percent was selected to be the true/false percentage threshold that all features must meet (Figure 12c). Table 1 also shows the number of features with less than 3.2% false positive and greater than 3.2% true positive detections (pink region in Figure 12c), for the three experiments at each water stress treatment. Therefore, this group of features (the grayed column from Table 1) was used to indicate the resulting stress location in the overall production domain under the machine vision system.

TPCA was found to be a meaningful water stress detection feature only during the first water stress cycle, when the plants were small in size. After applying the water stress, TPCA no longer was found to be meaningful. The treatment and control sets had already shown variations in plant size. The aim of the feature relationships was to suppress any variances in the feature, identifying the temporal relationship of that feature. Even though for TPCA this was not the case, other features were able to maintain consistent repeated detection of the applied water stresses. The repeated detection features for the all experimental data sets were the vegetation indices. For the first data
set the repeated detection features were \text{ENDVI}, \text{NDVIBlue}, the color feature Blue, and the textural feature Contrast. For the second data set, the repeated detection features were \text{ENDVI}, \text{NDVIRed}, and \text{NDVIBlue}. Three textural features (Energy, Entropy, and Homogeneity) only occurred once or twice in the later water stress cycles (#2 and #3) and at the lowest R^2 threshold level (0.87). The Third experimental data set did not find any textural feature to be meaningful. This suggests that the lettuce texture might be induced by a previously applied water stress and detectable at the older stage by the repeated water stress treatment. Because these textural features are meaningful at the lowest R^2 threshold, might suggest that the textural features are sporadic and it is at a lower threshold that the control’s values are suppressed with the more largely variant treatment values being easily detected. For the lower light conditioned experiments (#1 and #3) the color feature Blue was found to be a good indicator for the applied water stress. Whereas the higher light conditioned experiment (#2), the color feature Hue was found to be a good marker. The color feature Hue is a combination of the Red-Green-Blue channels and suggests that the high light levels makes these combinations meaningful than by the values themselves. Evaluating the various temporal relationships, all three experimental data sets had various amounts for the different relationships. The lowest feature count was for the coefficient of variation (relationship #6) with only 10 features combined from all experimental data sets. The highest feature count was evaluating the daily change (relationship #4) with a combined feature count of 39.
**Detection of Plant Stress Locality**

The sum of each identified feature for all control/treatment cells, during each 10 minute data interval, classified the severity. This does not indicate a water-stress severity, but instead the specificity of features counted amongst the cell, identifying the particular cell’s level of difference compared to the canopy zone. Figure 14 shows an example of the generated ROC curve from the first experimental data set. This curve identifies all of the varying specificity levels the user can choose from (when evaluating each experimental water stress data set). To better relate the data from the plots, three specificity levels were used for each experimental data set (100%, 67%, and 50%) indicating the number of features per cell to denote the severity. Table 2 identifies the total number of controls and treatments that were flagged as being severely different from the entire canopy during the one day applied treatments.

![Figure 14](image)

**Figure 14.** ROC curve plot showing the number of severe cells (for both Control and Treatment) at varying thresholds for the three water stress cycles. a) Identifies the overall first experimental results; b) Identifies the zoomed pink region from part a.
Table 2. Total number of control/treatment severe cells based on the threshold level of features found for each experimental run and water stress treatment.

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<th>Treatment</th>
<th>Control</th>
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It is desirable to choose the specificity level such that there are little to none of the control cells flagged as being severe but yet maintain a high count of treatment severe cells. The 100% specificity was a good indicator only for the second experiment’s second water stress treatment. For other experiments and stress cycles, it failed to mark treatment cells as severe. Likewise, the 50% specificity was a good indicator for the first experiment and the last water stress cycle of the third experiment, but allowed several control cells to be classified severe during the second experiment. Therefore, the 67% specificity level was used for the feature severity limit for the color coded graphical display, illustrating the stress locality in the production domain. Again, this specificity level was chosen due to the low control severity compared to the high treatment severity cell count and this specificity level is meant to be dynamic, chosen by the operator viewing the resulting images.
Figure 15 shows the first experiment’s third water stress treatment day’s events: a) identifies the number of cells that have a feature count, b) identifies the number of cells that are classified as severe, and c) is a canopy image identifying the cells severity and locality at the time the highest found severe cells are identified (marked as an arrow in parts ‘a’ and ‘b’ in the figure). In parts ‘a’ and ‘b’, the first vertical line denotes when the water stress was applied, the second vertical line denotes when human visual detection was made of the stressed plants, and for the third water stress cycle, the last vertical line denotes when the irrigation was returned to the stressed channels. Similarly, Figure 16 shows the second experiment’s second water stress treatment day’s events with the corresponding vertical lines to denote applying the water stress and when human visual detection occurred. The third experiment was only to ensure the validity that the varying light levels caused irreproducible results between the two experiments.
Figure 15. First experiment's third water stress treatment day with the water stress events identified as vertical lines (applied treatment, human visual detection, and water returned to the rows respectively). a) The cell count of both control and treatment to have feature values; b) The display of severe cell counts for both control and treatment; c) The graphical display of the canopy area identifying the stress locations at the designated arrow time (from part a and b).
Figure 16. Second experiment's second water stress treatment day with the water stress events identified as vertical lines (applied treatment, human visual detection, and water returned to the rows respectively). a) The cell count of both control and treatment to have feature values; b) The display of severe cell counts for both control and treatment; c) The graphical display of the canopy area identifying the stress locations at the designated arrow time (from part a and b).

Despite using the 3.2% detection threshold from the first experiment, when applying it towards the second and third experiment, the threshold performed well at detecting the treatment cells. Likewise, choosing a feature specificity count of 67% may not be applicable considering that the 50% specificity only failed for the second experiment.
The current study demonstrated a methodology for the selection of significant features and the selection of a specificity level. The threshold values might be different for a different crop or under a different environmental condition which was not evaluated in the current study. Therefore, expanding the experiment by improving the environmental conditions might be needed to verify these thresholds for a given crop and production setting.

**System improvements**

The performance of the water stress methodology was different based on the results obtained from three experiments and corresponding data sets despite the fact that the same plant was grown and the water stress treatment was applied at similar growth stages. This suggested that the stress detection methodology and the machine vision system were sensitive to the environment, resulting in the detection of different significant water stress features. For instance, Figure 17 shows the measured solar radiation intensities in the experimental greenhouse for the three experiment periods. In addition to the varying light levels, the existence of structural shadows amongst the plant canopy (Figure 18) might have caused errors in identifying the stressed zones. Minimizing the effect of light intensity and shadows especially for blob analysis was discussed in detail in Story and Kacira (2013). However the technique used did not improve the shadow removal on the plant or plant canopy, rather it helped minimize the effect of the shadow on the extracted data feature. One suggestion is to use the machine vision system within a greenhouse whose glazing material has a higher haze or diffuse
property. This type of glazing can allow the elimination of the structural shadows as well as increasing the light intensity uniformity, helping the computer vision system for image acquisition and improved image processing. Furthermore, integrating the thermal imaging with canopy temperature feature detection in the overall stress diagnostics along with other textural and morphological based features can help overcome the negative effects created by the structural shadows on the stress detection. An alternative approach can be the addition of an artificial light source during the image acquisition. This addition would also allow the possibility to establish night time imaging, increasing the length of the plant imaging capture ability to 24 hours per day. In addition, it is also desirable to include artificial neural network based modules to be integrated into the proposed stress detection methodology, creating a stressed plant/canopy imagery database to aid with the crop diagnostics.

![Figure 17. Varying environmental light conditions for the three experiments.](image)
CONCLUSION

This study successfully established a methodology, using a multi sensor based machine vision platform, to identify significant features separating the control and treatment plant group under an applied water stress. Then, the significant features were used to timely identify, amongst the plant canopy, the location of the emerging water stress. The system first statistically classified significant features, recognizing the emerging water stress between the control and treatment plants. From those features, an improved feature list based on the true/false detection percentage was developed allowing the monitoring system to identify amongst the canopy where deviations occur, tracking the emerging water stress. Plant cell severity has been ranked based on the number of feature counts for each cell. From this cell count, a graphical canopy image was
successfully generated. This image offers a representation of what a grower should see regarding the overall health and wellbeing of their greenhouse plants. Identifying where their time and resources are needed most in the production system.

The results showed that the performance of the machine vision system was affected by ambient light intensity and incidents of structural shadows on the canopy. The stress detection methodology was not able to replicate the same feature detection for similar stresses on the same plant. Attention must be paid to improve the image acquisition or the elimination of these negative environmental effects, thus several recommendations were made. The morphological feature, Top Projected Canopy Area, was found to be a significant marker for the initial growth period while the vegetation index features were more dominant at capturing the repeated stress occurrences during all stage of the lettuce crop. The crop’s canopy temperature was shown to be a significant and dominant marker to timely detect water stress. This feature can be given a higher weight factor for water stress detection and also to manage the negative effects of environmental factors on image passed feature extraction.

Greenhouse systems can be more resource use efficient if the environmental control system included plant responses measured in real-time with the decision making process. A decision support system that is capable of combining environmental data along with multi-sensor based canopy data must also be established to improve plant stress detection and identify causes of the various stresses.
ACKNOWLEDGEMENTS

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REFERENCES


APPENDIX C – WEB-BASED REMOTE EXPERT’S NETWORK DECISION SUPPORT SYSTEM

The third objective, to design and develop a web-based decision support system had been successfully created to dynamically collect, store, and analyze the greenhouse data to be displayed with the plant imagery. On this platform, various pages coexist, adding to the overall functionality of the site (http://cealive.arizona.edu/lgh/). The website is password protected such that each project team member had a login account, but the site did not have a SSL certificate, which would add to the level of site security.

The Overview page shows the latest collected values at a topographical level of the system. On this page, the user can visually identify what and where sensors are located, showing the latest value detected. Likewise, a graphical canopy data of the latest acquired image, identifying any abnormalities detected (Figure 1).

Figure 1. System Overview page of the Lunar Greenhouse Remote Experts’ Decision Support System (RENDSSys).
The Generate Reports page, the user can extract data to generate custom reports of the archival information stored on the platform. The data can be visually displayed on the website or in a downloadable Excel file. From this reports page, two subpages exist to identify real-time balances of resource inputs and outputs of the system. For the LGH chamber, it was important to identify water and carbon balances. Another subpage was the manual entering of data to maintain high levels of accuracy for the balance pages (harvest data, transplanting data, leak rate tests, etc) (Figure 2).

![Figure 2. Data entry page of the Lunar Greenhouse Remote Experts' Decision Support System (RENDSSys).](image)

The Manage Alarms page (Figure 3) allows the user to create an alarm based on the collected data. If the value becomes different than what is desired, the user can be notified of the change. The website emails the user the notification and if the user were to specify their cell phone email address, the message would be sent as a text message.
instead. It was necessary to limit to the amount of messaging done to once every 30 minutes, due to collecting frequent data, likewise triggering frequent alarms.

![Figure 3. Manage Alarms page of the Lunar Greenhouse Remote Experts’ Decision Support System (RENDSSys).](image)

The last two site pages are for file sharing and a message board (Figure 4). The idea behind these additions is for the sharing and collaborating of experts remotely, at a single location for everyone to be a part of, monitor the alarms and notifications, share inputs and comments for the posted notifications to help improving management of the LGH system.
Figure 4. Message board page of the Lunar Greenhouse Remote Experts’ Decision Support System (RENDSSys).