A Hyperspectral Imaging System for Plant Water Stress Detection: Calibration and Preliminary Results

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Abstract
Much progress has been made on optimizing plant water supply based on several methods of irrigation scheduling, in both open-field and greenhouse cultivations, such as real-time measurements of solar radiation and soil or substrate moisture. However, only a limited number of such methods use plant-based physiological indicators to detect plant water stress and adapt irrigation scheduling accordingly. In addition, even fewer indicators can be estimated by non-contact, remote sensors (RS) that do not affect plant development. Hyperspectral imaging technology could be an accurate remote way to detect moisture content of plants, taking into account crop characteristics. In this work, a methodology of hyperspectral imaging calibration and acquisition is presented. The method uses the reflectance characteristics in hyperspectral bands from 400 to 1000 nm and incorporates the appropriate radiometric and geometric corrections. The basic statistical parameters of mean and standard deviation values are used to estimate spatial and spectral correlation of each band on the extracted areas/pixels of interest. Several statistical techniques are used for the selection of optimal features that will lead to the development of appropriate plant water stress indices that could be used for incipient water stress detection in optimal irrigation scheduling systems.

Keywords: tomato, irrigation, early water stress detection, greenhouse

Introduction
Greenhouse irrigation management, especially on hydroponic systems, needs a series of short-time water applications (10-25 doses/day). Even though several methods are used to detect plant water deficit, only a few methods use plant-based physiological indicators. Katsoulas *et al.* (2006) stressed the need for the creation of a suitable method to control irrigation frequency and proposed a technique based on crop transpiration. However, that method implies the knowledge of a crop coefficient that varies for different planting periods.

Crop reflectance (Knipling, 1970), fluorescence (Norikane and Kurata, 2001) and thermal radiation transmittance (Jones and Schofield, 2008) are affected by water stress. Several studies have attempted to detect and quantify water stress -through relevant indices- using reflectance inside the visible and the near infrared regions (Peñuelas et al., 1993; Schlemmer et al., 2005; Sellers, 1985). The use of a hyperspectral camera to identify plant reflectance variations related to leaf water deficit levels is a non-destructive and fast measurement method. Hyperspectral imaging technology could be used to study leaf reflectance changes caused by different water stress levels in more than one leaf, enhancing the reliability and sensitivity of plant water detection (Graeff and Claupein, 2007; Sarlikioti *et al*., 2010; Zhou *et al*., 2011). Although remote sensing has been successfully used for years in open fields and relevant reflectance calculation models have been developed (Jacquemoud *et al*., 2009), it has not been extensively tested for greenhouse crops. It has to be noted that open field methods cannot directly be applied in greenhouses due to difficulties arising mainly from shadows casted by the greenhouse frame and equipment. The problems related to the greenhouse structure shadows or to disturbing factors (such as old leaves and soil background) could be overcome by combining data from two or more spectral bands to form vegetation indices (Jackson and Huete, 1991). According to Zakaluk and Sri Ranjan (2008), the most common forms of reflectance indices are the following: (1) reflectance ratios corresponding to the ratio of two spectral bands, which are referred to as simple ratio (SR) vegetation indices and (2) normalized difference (ND) vegetation indices, which are defined as ratios of the difference in reflectance between two spectral bands to the sum of the reflectance at the same bands.

Accordingly, aim of this work was to study the possibility to detect plant water stress in greenhouses using a hyperspectral imaging methodology and study the effect of system settings on reflectance measurements and plant water stress indices.

Materials and Methods

The hyperspectral camera Imspec V10 (Spectral Imaging Ltd, Finland) was used, which operates in the VNIR ranges of 400-1000 nm. It was used as a push broom line scan camera and provided full spectral information for each pixel. The hyperspectral camera was attached to a rotary scanning system, in which, scanning speed and angle were controlled. A spectral DAQ software was used to set the operational parameters of the camera, to start data acquisition and to monitor on-going tasks. The camera's specifications and settings were: spectrograph: V10, spectral range: 400-1000 nm, spectral resolution (30 mm): 2.08 nm, spectral resolution peak: 435.8 nm (2.86 FWHM/nm), 696.5 nm (3.34 FWHM/nm), 912.3 nm (3.33 FWHM/nm), slit width: 8 mm, pixels in full frame: 1312 x 1024, exp. time range: 0.1-500 ms.

The camera system was placed on a cart, so that images of the vertical canopy axis could be obtained. The hyperspectral imaging system was calibrated in a light control growth chamber. Light intensity was controlled with high pressure sodium lamps, 600W each. The chamber included 24 lamps in total (6 lamps per light-intensity level) with a maximum light intensity of 240 W m^{-2}. For extra illumination of the target area (70 x 100 cm), four quartz-halogen illuminators (500 W each) were used to provide calibration wavelength from 400 to 900 nm. The optic system was placed at 1 m from the target (white panel or plant). A spectrally flat black surface was placed as a background, to ensure a constant field of view without any shadows.

The calibration of the hyperspectral imaging system requires geometric and radiometric calibration (Lawrence *et al*., 2003). Geometric calibration eliminates optical errors, such as curvature disortion of the spectral lines. The system was already geometrically calibrated by the supply company. Radiometric calibration includes the elimination of a variety of noise sources, such as photon noise, thermal noise, read out noise and quantisation noise. The proper number of lens aperture (f/) and exposure time (ms) ranges of the camera for the specific light signal conditions were evaluated, in order to achieve the most suitable readout values. The MATLAB software package (by MathWorks®) was used for image analysis. The acquired images were improved based on the above factors, by using the radiometric equation:

$$r = \frac{R - D_\lambda}{W_\lambda - D_\lambda}$$

where: r is the actual plant reflectance, R is the measurement of plant colour reflection, W_λ is the colour reflection of the white reference in the specific lighting conditions during measurements acquisition and D_λ is the black reference (Polder *et al*., 2003).

Results

Images acquired with a hyperspectral camera contain noise from a variety of sources that are determined by the camera. Exposure time and size of lens aperture are some of the camera's parameters that can be used to eliminate signal-to-noise errors and improve the image sharpness. Figure 1 shows the dark current estimation based on the digital number (i.e., captured light intensity) response to different exposure time settings. As expected, dark current noise is proportional to exposure time values.

It was observed that the sensitivity of the CCD silicon detector is wavelength dependent (Fig. 2). Thus, the light signal showed low sensitivity in the blue part of the spectrum (high digital number values) and high sensitivity in the red and near infrared parts (low digital number values). The lowest values of noise were observed when the lens aperture was at 1.4 and the maximum values were observed at 11. Another interesting point is the dependency of the noise on the sensor temperature. Figure 3 shows the relation between sensor temperature and black level noise expressed by digital numbers. From this graph, it is evident that black level noise increases when the sensor temperature increases, following a 2nd degree polynomial trend line.

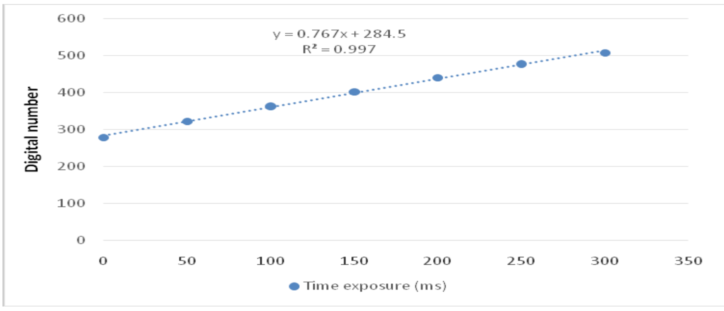

Fig. 1. Dark current noise estimation based on digital number response to different exposure times.

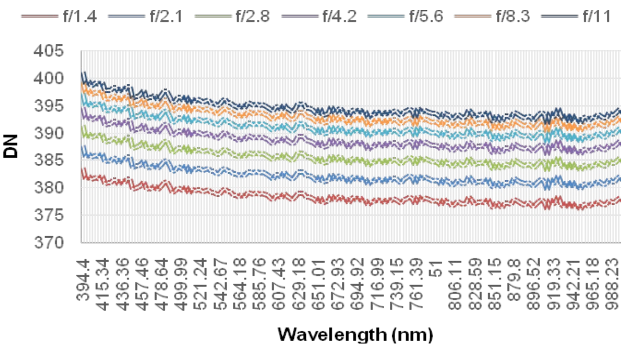

Fig. 2. Dark current noise development based on digital numbers response to different number of lens aperture.

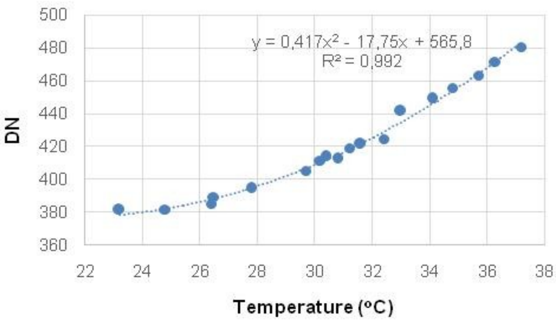

Fig. 3. Dark current development based on digital number response to different sensor temperature.

Before the acquisition of the hyperspectral images for the detection of water stress in greenhouse plants, the readout digital numbers of illumination in white reference for different exposure times were recorded. It was observed that the light signal of halogen lamps had a peak between 700 and 800 nm and tends to decrease at the left and right sides of the spectrum, as a result of the low values of light signal in the blue and infrared spectrum. The sodium lamps improved the light signal in the green and red spectrum, but the light signal in the blue spectrum remained low (Figure 4).

After all these procedures, the camera was used to measure plant reflectance and exact leave color measurements. In addition, the speed of the scanner had to be determined in order to avoid the distortion of image size and spatial resolution. The experiments showed that the images were clearer when the exposure time was 130 ms and the speed of the scanner was at 0.16 degrees with a frame rate of 500 Hz and a frame resolution of 800. The typical spectral signature of a healthy tomato plant is shown in Figure 5, for two different exposure times. The spectral signature of tomato showed differences between the two exposure times tested, due to the amount of captured light intensity through the slit. These variations will be further minimized in the analysis process, using various spectral indices. The combination of more than one spectral region reduces additive and multiplicative errors associated with light conditions. Some of the most effective spectral indices for plant water stress assessment are NDVI $((R_{680}-R_{800})/(R_{680}+R_{800}))$, rNDVI $((R_{750}-R_{705})/(R_{750}+R_{705}))$, mrNDVI $((R_{750}-R_{705})/(R_{750}+R_{705}-2*R_{445}))$ and PRI $((R_{531}-R_{570}/R_{531}+R_{570}))$. NDVI and rNDVI indices use steeply sloped regions of red edge and near infrared spectrum, which are more sensitive to smaller changes in vegetation physiology and are more suitable for hyperspectral sensors. NDVI and rNDVI showed the same index values between the different exposure time curves. The value of NDVI was 0.86 when the exposure time of the camera was at 140 ms, and 0.87 when the exposure time was at 130 ms. The values of rNDVI were 0.58 and 0.60, when the camera's exposure time was at 140 and 130 ms, respectively. mrNDVI also gave stable index values between the two curves, at 0.68 and 0.66, respectively. On the other hand, PRI seems to be more sensitive to light intensity and to environmental conditions, with decreasing values from 0.07 to 0.04 when the exposure time changed from 140 ms to 130 ms.

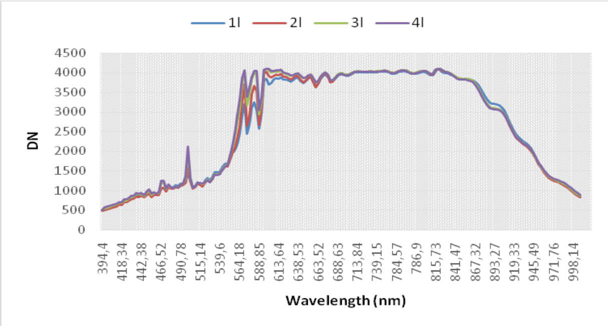

Fig. 4. Illumination reflectance for four different light levels (6 sodium lamps/level) at the same time, with 4 halogen lamps (Exposure time and lens aperture at 130 ms and f/2.1, respectively).

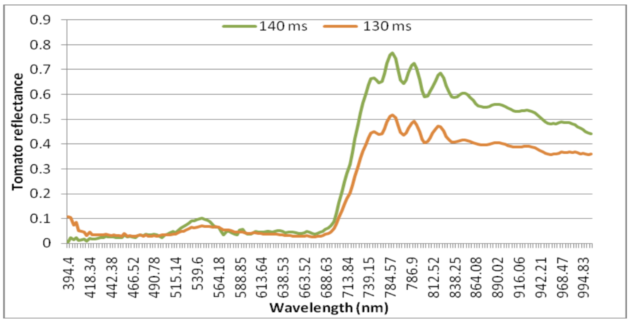

Fig. 5. Tomato reflectance based on the radiometric callibration method.

Conclusions

In this work, a hyperspectral imaging system was developed, to perform acquisition of hyperspectral imaging data and to estimate the optimal characteristic wavelength in order to create a predictable model of greenhouse plant water status. Different sources of hyperspectral camera's noise were investigated and the reflectance spectrum of greenhouse tomato was measured. Exposure time and lens aperture values were the camera's parameters that influenced the levels of dark current noise, which depended on light intensity. In addition, the dark noise current was increased by the increase of sensor temperature, following a 2^{nd} degree polynomial. It was validated that NDVI, rNDVI and mrNDVI indices are more sensitive to smaller changes in vegetation physiology and are more suitable for hyperspectral sensors. Finally, it was shown that PRI is more sensitive to light intensity and environmental conditions.

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