Leaf Inclination Based Non Destructive Water Stress Indication for Vegetables

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Abstract

In the present work a machine vision system is presented for analysing side projected canopy images of tomato plants. The images were taken by a digital camera in an experimental model greenhouse. The camera acquired images at user defined time-scales. The software measured the growth of the plants in vivo and in situ and focused on the leaf and stem edge inclination states under quasi-optimal and stress conditions. Stems were defined as all of the branches and petioles on the plant. ‘Leaf and stem’ inclination was calculated from the angle of the edge lines of the whole of the visible part of the plant canopy, including leaves, petioles and branches. Around each edge point there are a few pixel-long edge lines. The direction of these lines, located usually on the outside of the stems and leaves, are compared to the horizon. The general inclination value of the monitored canopy is counted from the direction of these lines in the range 0 to -90 degrees. This inclination value can provide non destructive information about plants’ wellness or stress condition. Besides irrigation the information thus gained can be used for setting optimal greenhouse parameters and measure plant growth.

INTRODUCTION

According to the International Food Policy Research Institute (2003) water use for households, industry, agriculture will increase by at least 50 percent in the next 20 years. Increased competition for water will severely limit the availability of water for irrigation, which in turn will price water to reflect its cost and value. It is important to check plants’ wellness regularly and keep them under optimal growth conditions.

Kramer (1983) stated that, at least in theory, plants should be the best indicators of need for irrigation. Plant water status can be studied best, either in terms of water content, cell turgor, free energy status, or water potential (Kramer, 1987). Watering plants according to their visual appearance is a traditional way of irrigation.

Seginer et al. (1992) followed the vertical movement of the tip of fully expanded tomato leaves using machine vision imaging and reported that the movement can be used as an indicator of incipient drought stress before the appearance of visual wilt symptoms. Side projected canopy images were taken from 60 cm tall tomatoes from a distance of 2 m. They reported a peak in the daily rhythmic leaf motion shortly after midnight. Their results suggested that leaf deflection is a sensitive and consistent measure of plant water potential. It is not an absolute measure, since each leaf responds differently, depending on its size and age, but it is a non-destructive, continuous and repeatable estimator of water potential over a period of several days. There was a linear relationship between the mean height of the leaf tips and the measured water potential. Young, not fully expanded tomato leaves exhibited vigorous motions, which was associated with the growth process. Tomato leaf deflection because of wilt was more easily observed on fully expanded leaves, whose other motions were more subdued. Trucking the leaf tips could provide information for triggering irrigation.

Another possibility of machine vision based plant water status estimation is to analyse the image of the canopy, rather than that of the individual plant, to get information related to the average water status. Kuruta and Yan (1996) extracted lines
reflecting inclinations of rachises of tomato plants from the whole canopy image obtained from a fixed position slightly above the canopy. The average direction of the extracted lines correlated well with water potential of tomato plants. The algorithm can be implemented in an automated irrigation system. One of the advantages of this method is that it also works when shadows of structural members of a greenhouse are cast on a part of the canopy whose image would be analyzed.

Nyakwende et al. (1997) set the camera above, and in front of a single tomato plant and used both top and side projected canopy images to detect water stress. Taut-string boundary and polygon area provided information about plant water status.

This paper deals with a non-destructive plant wellness monitoring system. In the experiment, plants’ well being state was interrupted with water stress. The visual reaction of plants was measured by the method described below.

MATERIAL AND METHODS

Model for Measuring Wilting

A model was created for measuring wilting tomatoes’ leaf inclination from lateral images where the subdued bottom leaves can be easily observed and analysed. The described method calculates leaf inclination, \( \theta \) in degrees, measuring angles between the horizon and local border directions of leaf blades (Fig. 1).

The algorithm looks for local edge directions on the canopy image and calculates their angle compared to the horizon. Directions are counted between 0° and -90° as the difference from the horizontal direction. Generally the bigger the wilting rate, the further the leaf blade direction is from 0° (horizontal direction) and the closer the leaf blade is to -90° (vertical direction). The model has a disadvantage in that it cannot distinguish between the directions which are symmetrical to the horizon. A turgid leaf with an upward (positive) direction would suggest the algorithm that the leaf is wilting, because it automatically converts the positive angles to negative (Fig. 1, \( \theta_c \)). As a result the developed algorithm works well for plants either in a quasi normal turgor state, a leaf inclination close to the horizontal or, under water stress conditions.

A machine vision system includes a video camera connected to a PC, and image analysing software. The side projected canopy images, displaying the plant conditions, are acquired via digital camera set at user defined time scales which the PC stores and analyses. The image analysing program has been developed using the C++ program language; it measures in vivo and in situ growth of the plant and continuously calculates the shape and size characteristics of the canopy, such as leaf inclination. The leaf inclination measuring algorithm is based on the methods of Tamura et al (1978). They researched the correlation between human vision studies and computational models of six textural features, including directionality. It was found that human studies corresponded well with the directionality model.

The Algorithm for Measuring Direction

The algorithm looks for edge or border pixels on the canopy image for example: where leaf blade points have local direction. The green pixels on the edge of the blade next to the white background can make a strong edge between the green and the white areas.

The magnitude \( |\Delta G| \) and the local edge direction \( \theta \) are approximated as follows:

\[
|\Delta G| = \frac{|\Delta_{V}| + |\Delta_{H}|}{2} \quad \theta = \tan^{-1}\left(\frac{\Delta_{V}}{\Delta_{H}}\right) + \frac{\pi}{2}
\]

where \( \Delta_{V} \) and \( \Delta_{H} \) are the vertical and horizontal differences among the greylevel values of the pixels on the image, measured by following 3 x 3 operators, respectively,
The resultant $\theta$ is a real number ($0 \leq \theta \leq \pi$) measured anti-clockwise so that the horizontal direction is zero. The desired histogram for directionality, $H_D$ can be obtained by quantifying $\theta$ and counting the points with a magnitude $|\Delta G|$ over the threshold $t$. Thresholding $|\Delta G|$ by $t$ is aimed at preventing counting of unreliable directions which cannot be regarded as edge points. Depending on the canopy colour, size, distance and lighting conditions the operator size and $t$ can be defined by the user. In these experiments the operator size was set to 5x5, with a pixel intensity of $t=180$.

On a canopy image horizon symmetric $\theta$ or $180^\circ - \theta$ would not make a difference, since it is not known which side of the leaf is connected to the plant. The $\theta > 90^\circ$ points were converted to the histogram as $180^\circ - \theta$ and multiplied by $-1$. In this way all the edge point directions are between $0^\circ$ and $-90^\circ$.

**Leaf and Stem Separation**

The program thresholds the image by using the average greylevel value of the edge points. The lighter points will be considered as background pixels. Of the remainder, the darker pixels will be plant points, either from the leaf or the stem. If any of the darker pixels is not recognized as a stem point, it is counted as a leaf point. It is assumed that the plant consists only of leaf and stem.

To separate stem points from the other pixels on the image, a matrix runs over the image and looks for stem characteristics. When the user defines $s_{\text{mat}}=5$, a $[2 \times s_{\text{mat}}+1, 2 \times s_{\text{mat}}+1]$ in this case an $[11, 11]$ pixel matrix is defined around a point (marked with a white X on Figure 2.) with 5 pixels distance from the centre.

The program runs the matrix over each point on the image and checks for stem pixels. To consider a pixel being a stem point, the pixel and the surrounding matrix has to fulfil 5 criteria. If any of these criteria is fulfilled, the pixel is not marked as a stem point and the algorithm checks the next pixel on the image.

**Criterion #1:** In Figure 2, from the 121 pixels there are 22 edge pixels, marked with white lines. The user can set the minimum amount of edge pixels $s_{\text{E}}$ in the matrix, to qualify a point as a stem pixel.

**Criterion #2:** In Figure 2. The average direction of the edge pixels is $(10 \text{ pixels } \times 90^\circ + 8 \text{ pixels } \times 89^\circ + 2 \text{ pixels } \times 45^\circ + 1 \text{ pixel } \times 60^\circ + 1 \text{ pixel } \times 70^\circ)/22=63^\circ$. The program calculates the difference between each direction and the average direction. By summarising the differences and dividing by the number of edge points in the matrix, will give the average direction difference. If it is smaller than the user defined value $s_{\text{diff}}$ then it is counted as 0. In the next step the program calculates (in percent) the average direction difference of the average direction. If it is smaller than the user defined $s_{\text{diff}}$ value, the second criterion is completed.

**Criterion #3:** The outside of the matrix should be lighter than the inside. In Figure 2, the $[4,9]$ point is on the right half of the matrix, and it’s right-hand side neighbour pixels are lighter than that on the left-hand side. The program verifies each of the edge points on the right-hand side, and on the left half edge points if their left-hand side neighbour pixels are lighter than that on the right-hand side. If it is true for a pixel, a counter value is increased by one, otherwise it is decreased by one.

In Figure 2 the $[7,9]$ point is on the bottom half of the matrix, and it’s bottom side neighbour pixels are lighter than that on the upper side, therefore a counter value is increased by 1. The program verifies all the pixels in the bottom half of the matrix.

The point $[7,2]$ is on the left half of the matrix, and it’s left-hand side neighbour pixels are lighter than that on the right side so the counter is increased by 1. But its bottom side neighbour pixels are not lighter than that on the upper side therefore the counter value is decreased by 1. In this example, after checking each of the edge points in the matrix, the counter will have a positive value, so the 3rd criterion is also completed.
Criterion #4: This criterion ensures that the centre pixel of the matrix is darker than it’s average. The given point must have a darker greylevel value than the average greylevel value of the surrounding matrix.

Criterion #5: The final criterion calculates the number of edge points, whose right side neighbour pixels are lighter than that on the left-hand side. It also calculates the number of edge points whose left-hand side neighbour pixels are lighter than that on the right-hand side. The ratio between the difference of these values and the number of edge points must be smaller than the user defined value, \( s_{zold} \). The number of edge points, whose bottom side neighbour pixels are lighter than that on the upper side are counted. The number of edge points, whose upper side neighbour pixels are lighter than that on the bottom side are also counted, and the difference between them is calculated. The ratio between the difference, and the number of edge points must be smaller than the user defined value, \( s_{zold} \). When the user defined value, \( s_{zold} \) greater than any of the two ratios, the 5th criterion is passed.

Directionality can also be applied for leaf points, if leaf and stem points are separated on the image (Fig. 3). The image analyser program maps the selected area, and the user can zoom to any part of the image. The info box window (Fig. 3) shows the magnified plant map to the user, marking the leaf and stem pixels with different colours. A square in the info window has the same colour as the magnified pixel from the encircled area. If the magnified pixel is an edge point, a tick inside the square shows its local orientation.

Wilting Measurements

The measurement took place in a model greenhouse where the camera was set 55 cm apart from the plants. Young tomato plants were grown in pots with soil, with approximately 11 cm as the top diameter and 9 cm as the bottom diameter. The height was approximately 10 cm. A 640 x 480 24 bit USRobot ic digital camera acquired images every hour. A Pentium 2 PC analysed images and saved the results. During the experiment a photoperiod (light/dark) of 14/10 hours was applied and in the course of taking images at night, an additional light was switched on. The experiment started at midnight and took 24 hours. Plants were last irrigated on the previous night, at about 11 pm. Leaf water content and leaf inclination was measured on tomato plants in the model greenhouse during the experiment. Control plants were used for observed measuring leaf water content: 7 leaves were cut off from the 5th and 6th branches, counting from the bottom to the top of the main stem. Their water content was measured with a Sartorius M40. The wilting rate of three other plants was measured by the method described above. All the measured plants were about 60 cm in height and located close to each other in the model greenhouse. When plants had visual signs of wilting, about 15:20 pm, they were manually watered with the same amount of water.

RESULTS AND CONCLUSIONS

Water stressed and irrigated plants were monitored while they recovered from wilted to turgid state Figure 4 shows measured values. Estimating the stem and leaf inclination results in a higher inclination value than measuring only the leaf inclination, because of the vertical direction of the main stems. As it can be seen on graph Figure 4, leaf inclination decreased when water content decreased. When the water stressed condition ended with irrigation, leaf inclination and leaf water content started to increase.

The algorithm was tested on tomato plants when leaves were partly hidden in the canopy. Tomato leaf deflection because of wilt was easily observed on the bottom and middle range leaves. The one day long experiment suggests that monitoring the bottom and middle part of the canopy can help in irrigation scheduling and in monitoring plants’ wellness. Applying the method, plant species and varieties, size, morphological features and developmental stage have to be taken into consideration. Upwardly oriented leaves (Figure 1, \( \theta_C \)) or stems disturb the measurement, since they are counted as if they were downward oriented. Concave leaf shape can influence the result when parts of the leaf
have a perpendicular direction to the leaf axis. Bending stems can move the leaf into a position where the subdued leaf is upside down and has a horizontal direction.

The units used to express water stress, and the method used to measure it, is applicable to a wide range of plant materials. The method is non-destructive, continuous and relatively inexpensive.

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Literature Cited


Figures

Fig. 1. Definition of leaf inclination ($\theta_a = -20^\circ$ $\theta_b = -40^\circ$ $\theta_c = -20^\circ$).
Fig. 2. Dark pixels represent the stem, the white lines show local directions.

Fig. 3. The user info window of the image analyzing program.
Fig. 4. Leaf water content, leaf inclination, leaf and stem inclination during the experiment.