AUTOMATED MACHINE VISION SENSING OF PLANT STRUCTURAL PARAMETERS

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ABSTRACT

Automated sensing of crop water stress is required to provide real-time variable-rate irrigation control that responds to spatial and temporal variability of plant water needs. Plant structural parameters such as internode length in cotton (i.e. the distance between successive main stem branches) are recognised as significant indicators of water stress level. This paper demonstrates the successful automatic identification of nodes and measurement of internode lengths.

A moving in-field camera enclosure involving plant contact was trialed in the (Australian) 2005/06 cotton growing season. The enclosure continuously traversed the crop canopy, collecting video footage of the cotton plants. The enclosure design utilises the natural flexibility of the growing crop to force (non-destructively) the plant's main stem onto a fixed object plane which enables the direct measurement of geometric dimensions without the need for stereo vision. Plant features are discriminated via processing of successive images to identify the main stem and branches, and hence stem-branch junctions ('nodes') are located. After confirmation that the plant structure is in the required object plane (by comparison of adjacent frames), the measurements of internode lengths are calculated. From fourteen sequences of images, with typically fifty images per sequence, main stem identification has been achieved in up to 88% of frames, and internode lengths have been measured with standard errors of 6% via automatic image processing and 3% via manual identification of nodes.

It is also demonstrated by analysis of the computational requirements that the necessary image processing can be undertaken in real-time. It is therefore concluded that on-the-go measurement of plant structural parameters is feasible and may be implemented at relatively low cost.

KEYWORDS. Algorithms, foliage, geometry, image processing, real-time system.

INTRODUCTION

The existence of spatial and temporal variability in agricultural fields means that there is potential for significant water savings via location- and time-specific irrigation application. Variable-rate application technologies exist for centre pivot and lateral move irrigation machines, however there is a need to develop real-time sensing tools to appropriately identify plant irrigation requirements.

In Australia the cotton industry is increasingly adopting centre pivot and lateral move irrigation. Plant structural parameters such as internode length (i.e. the distance between successive main stem branches) in cotton indicate water stress and the balance between vegetative and reproductive growth. Hence, this research aims to develop a vision system that automatically measures cotton plant structural parameters in the field in real-time, and that may potentially be used either in conjunction with variable-rate centre pivot or lateral move irrigation, or as an agronomic tool for automated measurement of plant growth in agricultural fields.

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Publicly-reported in-field vision sensing of plant parameters is currently limited to whole-plant or canopy-level measurements such as plant height, biomass and plant spacing (e.g. Praat and Bollen, 2004; Casady et al., 1996; Shrestha and Steward, 2005). In these applications, image processing successfully discriminated plant and non-plant (or background) pixels. Machine vision measurements that require discrimination of sub-plant features such as stems, petioles and leaves have been restricted to the laboratory environment, such as the machine vision system developed by Lin et al. (2001) to generate complete digital structural models of seedlings.

This paper reports a vision system designed for the purpose of measuring plant structural parameters on-the-go in the field environment. The system features a camera mounted behind a transparent panel in a camera enclosure, which continuously traverses a crop canopy (Figure 1). The enclosure makes use of the natural flexibility of the growing crop to firstly contact the transparent panel against the plant, and then smoothly and non-destructively guide the plant under the smooth, curved bottom surface of the enclosure. By forcing the plant into a fixed object plane (the transparent panel), reliable 2D geometric measurements can be obtained without the use of binocular vision.

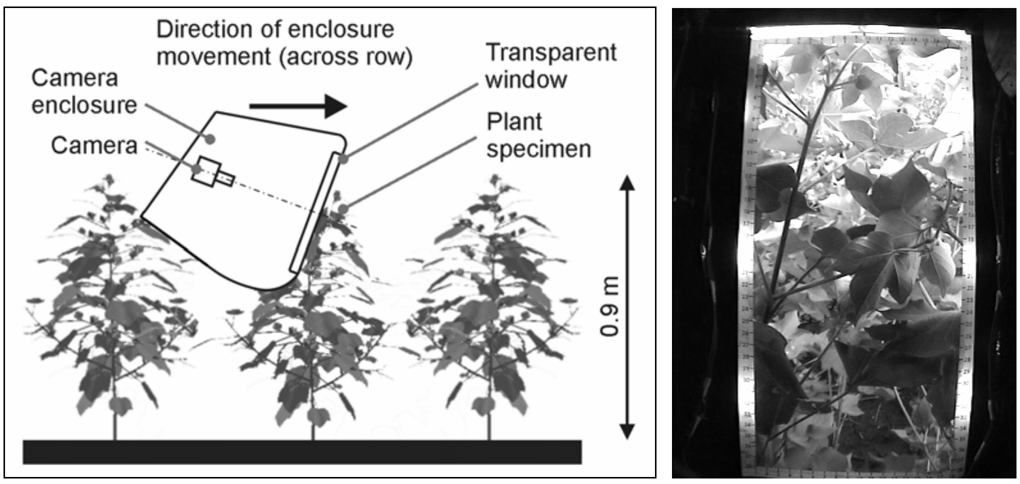

Figure 1. ***Left:*** **Moving image capture apparatus.** ***Right:*** **Sample image from apparatus.**

DATA COLLECTION AND FIELD MEASUREMENT SYSTEM

Image capture was via a Sony TRV19E camcorder (resolution of deinterlaced image: 720 x 288 pixels) mounted in a fibreglass camera enclosure with overall dimensions 520 x 290 x 520mm. The camera was mounted 350mm behind a window of effective image capture area 180 x 380mm. Image resolution at the transparent panel was found to be 1.0 pixels/mm in the horizontal direction and 0.6 pixels/mm in the vertical direction (with the camera mounted in ‘portrait’ orientation and hence a vertical raster scan). Focus was set manually to window scale marks (Figure 1). The weight of the camera enclosure was 6kg, and 8kg with the camera and computer equipment.

A manually moved enclosure was used to convey the camera across the cotton plants (Figure 2). The camera enclosure was suspended from a track mounted over the cotton rows and the enclosure’s height and yaw angle could be adjusted. Rotation of the enclosure about the yaw axis was necessary to enable the orientation of the enclosure to be changed after traversing to the end of the track, and also enabled the camera enclosure to be oriented either down or across the cotton row. For these initial trials, the preferred camera enclosure movement was across rather than along the crop row, due to the more sparse plant spacing across rows (one plant per metre compared with 10 to 16 plants per metre along row).

This prototype apparatus consisted of the camera enclosure suspended from a horizontal track that had an effective span of one row. The apparatus was manually placed about each target plant and adjusted for each plant’s height. The camera enclosure was manually pulled along the track to contact the target plant.

Figure 2. Manually moved camera enclosure in a cotton crop.

The imaging system was trialled on fourteen cotton plants (cultivar: Sicot 80B), ten weeks after planting during the 2005/06 Australian cotton growing season. The selected plants had many visible branches, including the main stem, in the acquired imagery. Direct physical measurements of the top five internode lengths were made for each plant targeted by the camera enclosure.

IMAGE PROCESSING AND INTERNODE DISTANCE MEASUREMENT

Plant features of stems and nodes are required to be identified from the acquired cotton plant imagery (Figure 1). Because the outdoor scene is subject to highly variable natural illumination, the image features non-uniform illumination and shadowing, stems range in colour from green to red and stems overlap with green leaves. Therefore the use of shape properties was judged to be more favourable than colour properties to identify stems in the image, since stems consistently appear as significant curvilinear structures in the acquired images.

The algorithm for identifying internode distance consists of both single and sequential frame analyses. Candidate nodes are firstly identified in individual frames, and then node trajectories formed by processing a sequence of frames (each video sequence consisted of one pass of the camera enclosure over a target plant). Sequential frame analysis is required since individual frames are subject to transient false candidate nodes caused by leaf edges, whereas over sequential frames, true nodes are consistently identified. A brief description of the process follows but a more detailed explanation may be found in McCarthy et al. (2007).

Main stem identification

Machine vision identification of stems in plant images was deemed visually similar to the identification of roads in aerial mapping images (e.g. Steger, 1996) and the identification of blood vessels in medical images (e.g. Frangi et al., 1998). Waksman and Rosenfeld (1997) used line detection to determine average petiole incline angle in vine images.

Frangi et al. (1998) and Sato et al. (1997) used Hessian matrix eigenvalues to calculate a ‘vesselness’ (or in the present case, stem-like) measure for each image pixel. If a pixel yielded one large and one small eigenvalue, the pixel was likely to belong to a curvilinear structure. This process was applied to the acquired cotton plant imagery to identify image points which were likely to correspond to stem pixels (typical results in Figure 3b).

The Hough transform (Duda and Hart, 1972) was used to fit a line to the ‘vesselness’ measure image to identify the main stem (Figure 3c). The Hough transform uses a voting system to identify collinear points in an image, and effectively detects lines even in the presence of large amounts of noise (Jain et al., 1995). The process assumes that the main stem is straight, a condition observed to be generally met in the acquired imagery. Main stem identification was achieved in 88% of frames using the developed process (McCarthy et al., 2006).

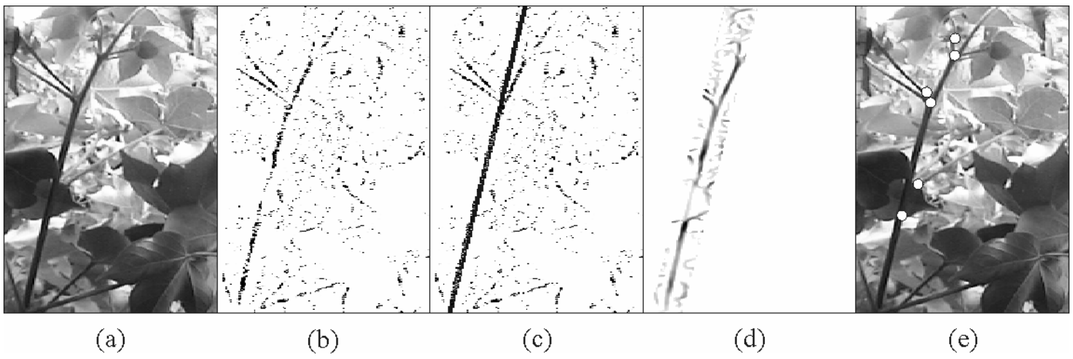

Figure 3. Steps to identify main stem and candidate nodes: (a) input image; (b) 'vesselness' measure image; (c) Hough transform line fitted to *(b)*; (d) Hessian matrix eigenvalues image to find main stem branch junctions; and (e) candidate nodes (white discs) superimposed on *(a)*.

<u>Node identification</u>

In McCarthy et al. (2006) node identification was implemented with moderate success via line detection for branches adjoining the main stem. In the present paper, identification of candidate nodes was achieved by identifying visible branch junctions (or 'v'-shaped junctions) along the main stem in the Hessian matrix eigenvalues image (Figure 3d). Node locations detected by this process are illustrated in Figure 4a. Figure 4a shows that there is a large number of falsely identified nodes, but most of the upper nodes are consistently identified. While 40% of candidate nodes were false positives, 86% of frames featured more than one correctly identified node. However, the sequential frame processing permitted the identification and elimination of false positives.

<u>Node trajectory analysis and internode distance measurement</u>

Figure 4 illustrates typical results for the extraction of true node trajectories from candidate node positions. Internode distance corresponds to the maximum distance between successive node trajectories, i.e. between trajectories B and C, and C and D in Figure 4d. From fourteen sequences of typically fifty images, a standard error of 6% was achieved for internode length measurement obtained using the image processing algorithm. This compared with manual identification of nodes for the same fourteen sequences which yielded a standard error of 3%.

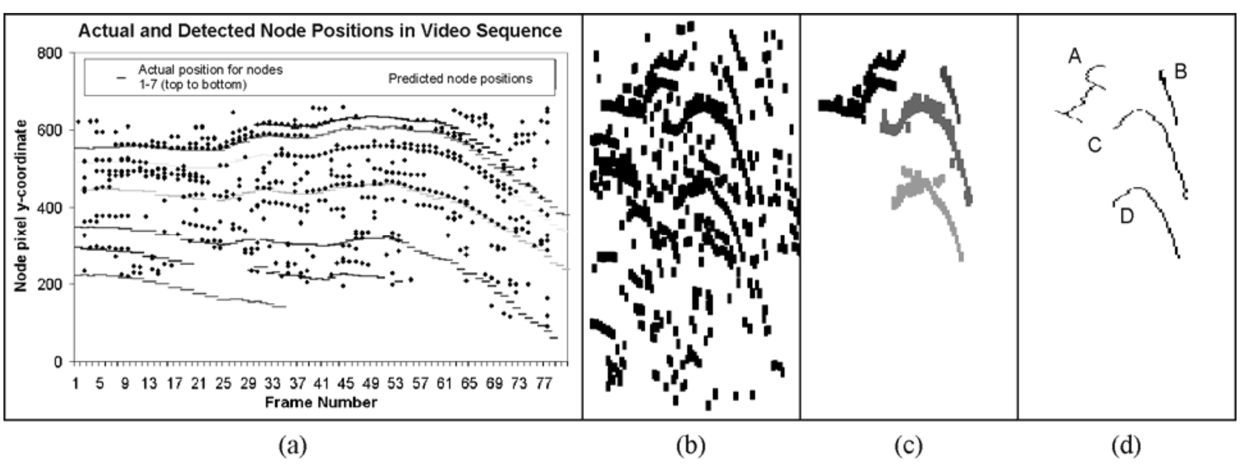

Figure 4. Sequential frame image processing to obtain single pixel thick node trajectories: (a) actual and detected node positions from single frame analysis; (b) morphological dilation of detected node positions to group neighbouring candidate nodes; (c) image *(b)* after removal of small areas; and (d) skeletonisation of image *(c)*.

POTENTIAL FOR REAL-TIME IMPLEMENTATION

The research prototype involved manual movement of the camera enclosure, post processing of data on a personal computer and only provided measurement of internode length as an output.

Hence, there are three areas of development required to convert the research prototype into a real-time imaging system which interfaces with other on-farm operations, namely:

- automatic conveyance of camera enclosure;
- real-time software execution; and
- interfacing with post processing and control actions.

Automatic conveyance of camera enclosure

A four-wheeled chassis supporting a camera enclosure track which spanned three cotton crop rows has been designed and constructed to allow for automatic movement of the camera enclosure (Figure 5). The chassis' propulsion and the camera enclosure's yaw angle, height and track traversal are driven by 12V DC motors. Operator control of the motors is implemented via a panel of electrical switches (manual motor control) or alternatively via software on a PICAXE microcontroller (automatic motor control). The system is powered by a 12V car battery with solar panel charging.

Figure 5. Automatic conveyance of camera enclosure in a cotton crop.

This automatic conveyance imitates an envisaged operation of the vision system where the camera enclosure may be mounted from a boom of a centre pivot or sprayer. While the manual apparatus was placed individually about each plant, the automatic apparatus spans multiple rows and hence may need to deal with variations in plant height and position from row to row. It is anticipated that further system development (e.g. adaptive camera enclosure height) will cater for row to row variations.

Real-time software execution

The image processing algorithms had an unoptimised execution time of approximately 400ms per frame on an Intel® Celeron® 1.40GHz processor, using the high level programming language Borland Delphi® 6.0 on a Windows XP operating system. The software had a significant graphical user interface (GUI) component. Removal of the GUI and optimised executable code will reduce the code execution time per frame, such that frame processing rate approaches the capture rate of 25 frames per second. Further speed improvements may be achieved by using an operating system optimised for real-time applications and parallel processing, as illustrated in Figure 6.

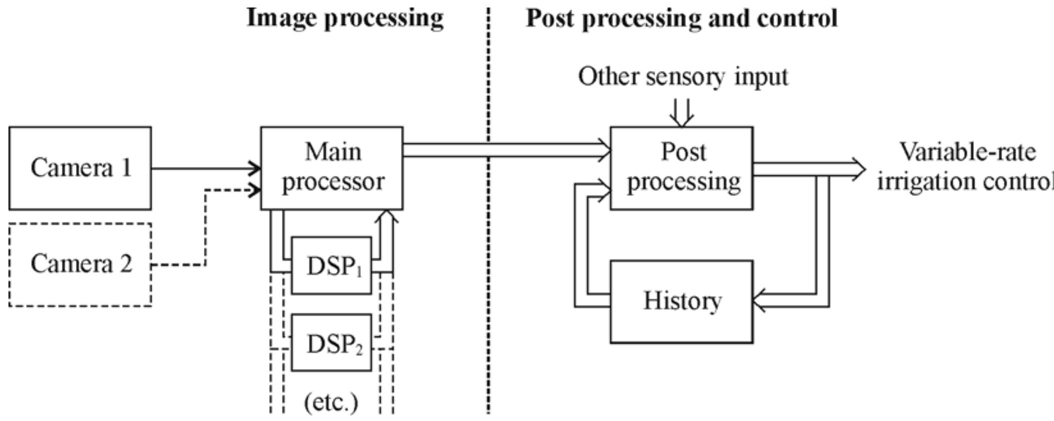

Figure 6. Conceptual block diagram of real-time imaging system (left hand side) and associated variable-rate irrigation control (right hand side).

Table 1 sets out estimated execution time for the major steps in the image processing algorithm, using a real-time software design that features a main processor and three digital signal processors (DSPs). The effective image area (corresponding to the window area) was rendered as 650 x 150 pixels (~10^5 pixels). The main processor receives a frame of image data from an image buffer, and identifies the effective window area. The image data in the effective image area is transferred to three DSPs (such as the A436 Parallel Video DSP Chip from Oxford Micro Devices) which concurrently perform two Gaussian and derivatives of Gaussian convolutions on the image data (as required for the Hessian matrix eigenvalues calculations). The convoluted image data is transferred back to the main processor, which then completes the remaining steps involved in identifying the main stem and candidate nodes. After the camera enclosure has completed the pass over the plant, the main processor calculates internode distances for the plant.

The total estimated algorithm execution time is 50ms per frame, which would allow a real-time video capture and analysis rate of 12 frames per second. However, a true algorithm execution time could only be obtained by coding the algorithm using the instruction sets of the actual processors chosen for the real-time design.

Table 1. Estimated code execution time for possible real-time implementation of image processing, based on a cycle time of 10ns for the main processor and DSPs, a DSP data transfer speed of 300Mb/s and use of three DSPs for parallel calculation of the Gaussian convolutions (for the Hessian matrix eigenvalues calculations).

Step	Process	Estimated execution time (ms)
Single frame image processing		
1	Mask for window area and grayscale conversion	1
2	Transfer image data from main processor to DSPs 1-3 (in parallel)	3
3	Parallel Gaussian and derivatives of Gaussian convolutions on DSPs 1-3 (image rows)	10
4	Parallel Gaussian and derivatives of Gaussian convolutions on DSPs 1-3 (image columns)	10
5	Transfer convoluted data from each of DSPs 1-3 to main processor	8
6	Calculate eigenvalues	1
7	Calculate 'vesselness' measure	1
8	Hough transform	1
9	Node identification	15
	Total estimated execution time per frame	**50ms**
Sequential frame processing		
10	Morphological dilation, connected component labeling, removal of small areas and thinning	2
	Additional estimated execution time per sequence	**2ms**

Interfacing with post processing and control actions

The existing image processing algorithm provides measurements of internode distances. A practical agricultural tool requires such data to be interpreted in terms of the plant irrigation requirement, or some other relevant control application.

Variable-rate irrigation control

The envisaged operation of the developed sensor is for integration with a variable-rate centre pivot or lateral move irrigation machine which adapts water output in response to sensed plant irrigation requirement. Such a variable-rate system requires data from a variety of environmental sensors including soil moisture sensors, remote sensing images and meteorological conditions, and also requires a decision support system to integrate data and determine irrigation amount.

Using the IEEE 802.15.4 wireless standard (with a transmission rate of 250kb/s), and transmitting a 50-byte data packet consisting of internode distance and GPS data, the imaging system would be able to log data to a central database and request that the decision support system calculate and issue a command for a particular irrigation amount at the current GPS location. Table 2 sets out estimated execution times for these operations, which suggest that the imaging system must be physically at least six seconds ahead of the variable-rate irrigation application.

Table 2. Estimated post processing execution time for variable-rate irrigation command

Step	Process	Estimated execution time (ms)
1	Time for one pass of camera enclosure over plant (across row)	3000
2	Wireless transmission of each data packet (internode distance and GPS data) from imaging system	2
3	Decision support system accesses database and calculates irrigation amount	1000
4	Wireless transmission of command for irrigation amount to irrigation machine	2
5	Variable-rate nozzle response time	2000
	Total estimated time for control sequence	**6004ms**

Other potential post-processing and control applications

The devised automatic imaging system, capable of in-field identification of sub-plant features and potentially identification of topological positions of plant structures, has possible uses beyond irrigation control. These include the following:

- Use as part of a sensor for nutrient deficiencies for the purpose of variable-rate nutrient application. If the system identifies leaves at specific locations on a plant, the addition of a second imaging device (Camera 2 of Figure 6) with differing spectral characteristics will permit identification of symptomatic discolouration of individual leaves associated with nutrient deficiencies. In this case, test discolouration patterns could be stored on-board such that external database access is not required, hence the major time component would be actuation of a variable-rate nozzle.
- Automatic guidance for sensors such as infrared thermometers, which require precise placement to target individual leaves. Placement of the sensor to required mechanical position may take of order one or two seconds which would permit its use for real-time irrigation.
- Correlation between ground-based plant growth measurements (taken with the automated vision system) and management zones identified in remote sensing images, which would enable a physiological interpretation and/or ground truthing of the remotely sensed images.

CONCLUSION

The feasibility of a real-time, on-the-go machine vision sensor for plant structure has been demonstrated. By considering sequential frames of a video sequence, internode distance measurement was successfully achieved using automated image processing algorithms. However, further algorithm refinement is required to achieve routine measurement at the desired accuracy.

Considerations for transferring the system from a research prototype to real-time implementation as an on-the-go agricultural tool include image processing computation time and integration with other sensors. The system was designed for use as an irrigation requirement sensor but other potential applications include nutrient deficiency identification and ground truthing of remote sensing imagery.

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