Applied machine vision of plants – a review with implications for field deployment in automated farming operations[1]

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Abstract

Automated visual assessment of plant condition, specifically foliage wilting, reflectance and growth parameters, using machine vision has potential use as input for real-time variable-rate irrigation and fertigation systems in precision agriculture. This paper reviews the research literature for both outdoor and indoor applications of machine vision of plants, which reveals that different environments necessitate varying levels of complexity in both apparatus and nature of plant measurement which can be achieved. Deployment of systems to the field environment in precision agriculture applications presents the challenge of overcoming image variation caused by the diurnal and seasonal variation of sunlight.

From the literature reviewed, it is argued that augmenting a monocular RGB vision system with additional sensing techniques potentially reduces image analysis complexity while enhancing system robustness to environmental variables. Therefore, machine vision systems with a foundation in optical and lighting design may potentially expedite the transition from laboratory and research prototype to robust field tool.

1. Introduction

Farm managers typically include visual assessment of crop condition to inform management decisions (e.g. irrigation timing) and treat the whole field uniformly based on their manual observations. For example, internode length measurement (i.e. the distance between branch junctions) is part of a plant-based water stress monitoring regime for cotton suggested for growers (Milroy et al., 2002). A machine vision system with access to a large proportion of the field potentially enables automatic condition assessment for different plants at high spatial frequency in the field. Such sensing capability, in conjunction with the implementation of appropriate variable-rate application hardware, potentially enables agricultural fields to be treated as a conglomerate of control units for operations such as irrigation and fertigation

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(e.g. Smith et al., 2009). Over a decade ago it was recognised that sensors are required to be developed to use as input for variable rate systems (Evans et al., 1997b) and machine vision-based sensing systems are a major part of this development. Other potential applications of machine vision systems in the field cropping environment include yield estimation and species identification.

As a potentially low-cost technology with low risk of mechanical failure, machine vision is particularly suited to the agricultural environment in which large numbers of sensors may be needed to cover an area of the field and robustness and ease of replacement are forefront design factors. In its simplest form, the conceptual vision system may consist of a single monochrome or colour camera with image analysis algorithms developed to identify the crop feature of interest under a range of environmental (e.g. lighting) conditions. However, refinements to the vision system such as stereo vision, multispectral imaging and range sensing potentially enable accentuation of features of interest in captured data while reducing the effect of environmental factors on image quality. Potential advantages of this are simpler and more reliable data processing.

The design of a vision system for the measurement of plant attributes is affected by many factors, such as the scale of the plant measurement (i.e. leaf- or canopy-level) and the measurement environment (e.g. a laboratory or in the field). Outdoor and indoor environments are distinguished in this review to enable comparison of systems subject to variable natural daylight with the (significantly lesser) challenges for systems operating in controlled-illumination environments.

1.1 Outdoor vision systems

Vision systems developed for measuring plants in agricultural fields are commonly required to analyse spatial patterns, i.e. discriminate differences, at the field scale, and hence are required to perform with high resolution. The goals of such analyses include yield prediction/monitoring and the evaluation of crop management practices. The task of measuring an adequately representative sample of plants within a field implies the acquisition of considerable quantities of data. Whilst this no longer presents computational difficulties, both the complexity and the speed of data acquisition usually required implies complete automation of the sensing task. However, the outdoor agricultural environment presents complexities that make such automation challenging. These complexities include variable natural lighting, both intensity and direction, and the occlusion and obscuration of plant features by foliage from neighbouring plants and background material.

Early vision systems for agriculture involved automation of fruit identification for harvesting, possibly because fruit was distinctly coloured and thus readily distinguishable from foliage (Tian & Slaughter, 1998). However, broad spectral wavebands are not as useful for discriminating objects in scenes comprising predominantly green foliage. Du et al. (2007) concurred that for species identification, environmental factors caused leaf colour to be of low reliability. Subsequently, Du et al. only used leaf shape features in an automatic species classifier. Similarly, Jimenez et al. (2000) reported that vision systems based on shape were less sensitive to variation in target object colour, but that shape analysis algorithms were more time-consuming. This suggests that where possible, vision systems designed for the outdoor environment should consider methods of automatically controlling and calibrating colour measurements and/or accentuating shape features to enhance reliability.

1.2 Indoor vision systems

Controlled indoor environments (e.g. laboratories and factories) remove many of the variables that complicate outdoor agricultural machine vision systems. Applications of machine vision systems to plants in the greenhouse/laboratory environment include automatic irrigation management, fruit harvesting and flower grading. Under laboratory conditions, lighting and positioning of free-standing individual plants may be controlled, so the drawbacks of variable natural sunlight, irregular spacing/location of plants and complicated image backgrounds are often minimal. As a result, the ability to control the environmental conditions in an automated laboratory irrigation system means that small changes in intricate plant geometric relationships can be detected on a continuous time scale and attributed to a particular cause (such as water stress), capabilities which have not yet been successfully transferred to the outdoor environment.

1.3 Paper overview

This paper firstly reviews the literature of machine vision-based plant sensing techniques for automation of measurements of living plants in both outdoor and indoor environments: the literature is considerable, hence only those considered significant by the present authors are cited. The work reviewed is considered by division into four broad sensing techniques, namely:

- monocular vision with an RGB camera;
- stereo vision and 3D structure;
- multispectral imaging; and
- range sensing.

The paper then proposes that intuitive sensor combinations and lighting design in a machine vision system may accentuate features of interest in the captured image and greatly enhance system robustness in the outdoor environment. In general this necessitates additional optical and/or mechanical components be added to the system to condition the scene, but this increase in system complexity is balanced by the benefit of reduced complexity and enhanced reliability in the subsequent image analysis. The paper concludes with a summary of potential methods to enhance the machine vision system design for application to the agricultural field environment.

2. Monocular vision with an RGB camera

In its simplest form, a vision system consists of a single camera capturing a naturally-occurring scene, such that the captured image resembles the scene as visible to a human.

It follows that there is potential for image analysis algorithms to extract objects in the image that are identifiable by humans. This entails implementation of colour and shape detection algorithms, and almost always adaptive optimisation procedures in situations where constant and uniform algorithm parameters do not perform adequately on images subject to varying illumination.

2.1 Outdoors

Common outdoor applications for machine vision of plants using monocular vision include plant counting, biomass estimation and species identification. These applications require that plant pixels be reliably extracted from non-plant or background pixels. Segmentation may be achieved by a variety of methods, from analysis of natural scenes to analysis of scenes conditioned by additional mechanical and optical components, for the purpose of less complicated segmentation algorithms. Shape and size algorithms may be applied to describe individual leaves following the segmentation process, as reviewed below.

In the following subsections, a ‘natural’ scene refers to one in which the image objects appear as they do everyday to humans. A ‘conditioned’ scene refers to one in which additional mechanical and/or optical components have been used to accentuate features of interest and/ or remove background elements in the scene, such that the captured, unprocessed image no longer looks ‘natural’ – to a human, at least.

2.1.1 Segmentation in natural outdoor scenes

Segmenting foliage from background soil (in top-view images) is an important first step in the automated image analysis of crops (e.g. measurement of lettuce head diameter, Hussain et al., 2008). In images captured of natural scenes, objects and their backgrounds often exhibit common intensities which reduce the effectiveness of a monochrome threshold (Tian & Slaughter, 1998). Ewing & Horton (1999) speculated that diffuse lighting from cloudy days may provide better illumination of leaves which would otherwise be in shadow on a clear day. Methods of segmenting vegetation in outdoor scenes using visible colour include those developed by Woebbecke et al. (1995), Tang et al. (2000) and Steward et al. (2004).

Multiple small plants are generally extracted as a single object if the foliage of neighbouring plants is touching. However, Soille (2000) extracted clusters of leaf vein regions from top view images to isolate individual plants with overlapping leaves; whereas Jin & Tang (2009) used stereo vision to isolate individual plants by attributing different leaf heights to different plants. Individual leaves are potentially extracted from leaf clusters using methods based on shape (e.g. using the ‘watershed algorithm’, Lee & Slaughter, 2004) and colour (e.g. using genetic algorithms – Neto, Meyer & Jones, 2006). Shearer & Holmes (1990) used texture analysis of plant top views to achieve canopy characterisations without extracting individual leaves.

In some situations the camera can be positioned to take advantage of naturally-occurring silhouettes of crop canopies. For example, leaf area index (LAI) measurements using hemispherical photography (e.g. Jonckheere et al., 2004) consist of a skyward-facing camera placed beneath the canopy, such that the foliage is backlit from the sky and clouds. The segmentation task involves methods such as automatic thresholding and edge detection (Ishida, 2004; Nobis & Hunziker, 2005). In a vineyard, Williams & Ayars (2005) estimated overall canopy dimensions and crop coefficients from images of the ground. Row spacing enabled observation of the shadows of individual rows cast onto the ground at solar noon and shadow pixels were counted (with a manual threshold on pixel intensity) as an indication of canopy biomass. The success of these systems is dependent on specific meteorological conditions but the applications demonstrate effective use of natural lighting to reduce complexity of image analysis.

McCarthy et al. (2009) relied on natural lighting conditions to estimate cotton plant internode length in a maturing crop and found that the system performed most reliably under diffused afternoon sunlight with the camera facing a direction perpendicular to the sun's rays. The system featured a plant-contacting camera enclosure that non-destructively forced the plant's main stem into a fixed object plane (i.e. the front of the camera enclosure) such that geometric distances could be automatically measured. Shape-based image analysis techniques were used to discriminate branches of individual plants and node positions were confirmed by analysing candidate node positions over multiple sequential frames. In this situation, use of a time series of images enhanced the system's accuracy.

2.1.2 Segmentation in conditioned outdoor scenes

Modification of a standard CCD camera to remove the infrared-cut filter presents another alternative for segmentation of vegetation from background soil. Vegetation pixels can be estimated using NDVI (Normalised Difference Vegetation Index) because vegetation has a higher reflectance than soil in near-infrared wavelengths (Kumar et al., 2001). The use of low-cost components potentially contributes to the appeal of this approach. Noh et al. (2005) also reported that the infrared channel was useful for segmenting vegetation.

The software segmentation task may potentially be simplified with the addition of mechanical components, particularly for cameras imaging the side view of canopies. A mature vineyard canopy is particularly suited to on-the-go machine vision measurement with sideways-facing cameras due to the spacing between rows, which enables a camera and backing board to fit comfortably on either side of the canopy, such that a side view of the foliage can be obtained. Such a system was implemented by Praat et al. (2004), with biomass being estimated by counting green vine pixels and discounting the distinctly-coloured background board.

Implementing an on-the-go infield vision system with controlled background is more difficult for individual larger plants in row crops. In a developed rice canopy, Casady et al. (1996) manually positioned a portable frame and shroud about each plant to segment foliage pixels and successfully measure biomass. In view of these difficulties Tarbell & Reid (1991) chose to transport mature individual corn plants from the field to a laboratory to conduct image capture. In a system collecting top view images of corn, Noh et al. (2005) performed colour calibration of foliage in the field by including a reference panel in the field of view of the image. The reference panel was painted with grey shades of known reflectance for comparison with the foliage and permitted nitrogen deficiency to be estimated under a range of natural lighting conditions.

For small plants, lighting conditions can be artificially controlled by mounting a lightproof cover from a tractor or mobile robot, in order to control lighting conditions of the plants under the cover during imaging in the field (e.g. Edan et al., 2000; Hemming & Rath, 2002). This is more difficult for larger plants, since apparatus that sufficiently encloses each plant will potentially restrict on-the-go operation of the device. Therefore, it may be expected that a shade structure for larger canopies will potentially dominate, but not completely eliminate, the effect of external lighting conditions.

2.2 Indoors

In a controlled indoor environment, single-camera systems can potentially identify small changes to foliage orientation and colour in plant canopies. This has potential application to irrigation scheduling. Identification of different plant parts in cuttings can also potentially be achieved with application to the estimation of plant quality attributes such as stem-to-leaf ratio.

Canopy changes due to induced stresses can also be isolated by signal processing from plant diurnal movement and growth. Irrigation scheduling systems have been developed using leaf tip tracking for wilt detection (Seginer et al., 1992) (manual system), change in side projected area (Murase et al., 1997) and change in top projected area (Kacira & Ling, 2001; Kacira et al., 2002). In these applications, the plant parameter of interest is isolated from a binary image in which the plant is segmented from the background. These systems tend to focus on detecting small differences in geometry such as leaf inclination. Similarly, Zeng et al. (2008) used a backlighting board mounted behind individual grapefruit to continuously monitor diameter changes. Techniques devised for automated laboratory systems have potential application in sustainable biosystems for space, e.g. research to develop automatic irrigation and management systems for crops on space missions (Fleisher et al., 2006).

Identifying the onset of water stress using petiole wilt detection in a vine canopy was evaluated by Waksman & Rosenfeld (1997). The average petiole angle was extracted from greyscale vine images using line detection techniques and results from images with the light source in different positions were combined in order to reduce occlusion by shadows. Kurata & Yan (1996) calculated the average incline angle of rachis (the central axis of compound leaves) lines in tomato plants to estimate water potential. Waksman & Rosenfeld (1997) also studied colour distribution in plant leaves to identify paleness, and hence the onset of stress. Tarbell & Reid (1991) conducted a laboratory study to compare foliage colour of mature corn plants with colour charts and to measure leaf area from plant silhouettes on a light stage.

Machine vision research for grading of plant cuttings in the geranium (Humphries & Simonton, 1993; Singh & Montemerlo 1997) and sugar cane (Wang et al., 1998) industries demonstrate plant part identification in controlled imaging environments. Both colour and binary shape relationships can be used to identify flowers, leaves, petioles and stems in plant cuttings for the purpose of determining flower size and stem-to-leaf area ratio, for example. For larger plants, Hemming et al. (2005) used an air blower system to distinguish leaves, fruit and stems in a tomato canopy with a distinctly-coloured background. Leaves were identified as those objects which moved with the air stream, while fruit and stems remained relatively motionless.

2.3 Discussion

Automated machine vision sensing of individual plants in the field is at present mostly limited to early stage crops (where neighbouring plants are too small to be touching or overlapping); or, for more mature canopies, to whole-plant characteristics such as plant biomass. Use of near-infrared imaging, background boards and/or shade structures with artificial illumination reduce the complexity of the segmentation process but add extra components and potentially physical bulk to the overall measurement system.

In the indoor environment, a monocular vision system can identify small canopy changes for irrigation scheduling purposes. However, it is likely that additional sensing techniques and technologies are required to make equivalent on-the-spot irrigation scheduling judgements in the outdoor field environment.

3. Stereo vision and 3D structure

Stereo vision can be used to monitor plant parameters including height, leaf shape and leaf area for young plants and overall canopy dimensions for larger crops. Automated measurement of 3D plant structure has application to crop and plant growth monitoring and species discrimination.

3.1 Outdoors

Differentiation of distinct plants (e.g. crops and weeds) is a difficult task in 2D that requires delicate image analysis but is greatly simplified with depth information (Jin and Tang, 2009). Three-dimensional maps of canopy structure were obtained by Rovira-Mas et al. (2005) using aerial stereoimages captured from a remote-controlled helicopter with GPS. The generated maps contained information about the distance between crop rows, the location of crop rows and the height of the crop. This application potentially enables appraisal of crop condition at high spatial resolution. Over a large area, a single high-resolution image of the field can be accumulated by image mosaicing. Image mosaicing or sequencing involves a moving camera capturing top view images (for example) of a crop row and then automatically identifying where consecutive images 'stitch' together, using matching algorithms (e.g. Kise & Zhang, 2006).

Methods of inferring 3D plant structure without image matching have been demonstrated in the literature. Images of trees captured from multiple angles are used to reconstruct 3D bounding geometry, also known as the visual hull (e.g. Shlyakhter et al., 2001). However, the method does not provide information about the plant structure deeper within the canopy. Dror & Shimshoni (2005) demonstrated the potential to infer within-canopy 3D structure of a palm tree from a single image using plant phyllotaxis. Plant phyllotaxis is the arrangement of repeating units in a plant, such as the divergence angle of consecutive leaves or branches. Therefore, image-based identification of plant phyllotaxis has potential to assist real-world plant geometry calculation.

3.2 Indoors

Typically smaller plants with less dense canopies have greater success of detailed automated 3D measurement. Andersen et al. (2005) generated 3D reconstructions of young wheat plants automatically from stereoimages. Chien et al. (2004) and Chien & Lin (2005) used three mutually perpendicular views (two sides and one top) of vegetable seedlings to measure 3D plant structure including leaf area, leaf number and internode length. This enabled the generation of continuous growth curves under various conditions. The top view provided the most information but the side views permitted correction to leaf area estimation where leaves were tilted.

Stereo matching for plant structure at post-seedling stage is limited even with a plain image background in controlled indoor conditions. Pan et al. (2004) created a semi-automated stereoscopic matching algorithm in which corresponding points were automatically identified by image analysis but were required to be refined by a human operator. However, Takizawa et al. (2005) enhanced automation by extracting leaf and stem regions and then using those regions to perform matching between stereoimages. Matching of stem regions for rose plants was restricted when stems were in front of leaves instead of the plain background or when the stem was visible only in one image of the stereoimage pair (Noordam et al., 2005).

3.3 Discussion

As with monocular imaging, identification of plant structure using stereo vision enjoys greater success for smaller plants. Applications in the outdoor environment typically provide overall canopy geometry which is useful for monitoring crop growth in areas of a paddock or identifying plant height changes, for example between different species (i.e. weed and crop).

Determination of leaf and branching structure of individual plants is limited even in indoor environments and relies on the image having a plain background. Knowledge of plant growth patterns (e.g. phyllotaxis) potentially assists measurement by image analysis.

4. Multispectral imaging

The sensing and image analysis task may potentially be simplified by imaging in part of the electromagnetic spectrum which accentuates features of interest more effectively than the broad visible bands provided by standard RGB cameras. Sensing of different regions of the electromagnetic spectrum potentially enable discrimination of plant materials based on colour (visible), cellular structure (near-infrared, NIR), thermal (mid-infrared, MIR) or hardness (X-ray) properties.

4.1 Outdoors

4.1.1 Species identification

Humans perceive colour in three broad channels of red, green and blue, whereas plant species may potentially be discriminated by higher-precision colour measurements. Significant discriminatory wavelengths between weeds and crop can be used in a classification model to achieve recognition (e.g. Vrindts & de Baerdemaeker, 1997). The sensing system may be in the form of a point, line or imaging sensor. Wang et al. (2001) implemented a five-wavelength system using phototransistors to measure reflected light.

4.1.2 Plant material identification

Sophisticated multispectral imaging technologies have been applied to machine vision research in agriculture. Stajnko et al. (2004) identified apples in orchards using thermal imaging of trees in the late afternoon to achieve a temperature gradient between the fruit and the background whereas Safren et al. (2007) used a hyperspectral image acquisition system featuring an acousto-optical tunable filter (AOTF) and principal component analysis to identify fifteen spectral bands from 500 to 900 nm that adequately discriminated green apples from leaves in an apple orchard. This research provides useful information about spectral properties but the expense of the sensing systems limits its routine deployment on-farm.

A portable X-ray source was used by Haff & Slaughter (2009) to successfully identify stems through leaves of standing plants in a tomato plantation. The X-ray source and detector were mounted on either side of the crop row and inside a metal 'tunnel' which provided directional X-ray protection for personnel and enabled the apparatus to move continuously along the row of plants.

4.1.3 Stress detection

Carter & Miller (1994) found that herbicide-induced stress could be detected with colour and narrowband digital imagery. They captured digital images of soybeans around midday and included five grey reference cards to calibrate each image. Narrowband interference filters were used to isolate spectral bands in the images.

Colaizzi et al. (2003) developed a spectral reflectance and infrared thermometer sensing system on a track on a linear move span to deliver spectral images at four bands and high spatial resolution. Leinonen & Jones (2004) combined visible and thermal imaging to identify regions of interest in a thermal image of plants (e.g. by isolating plant from soil pixels).

4.2 Indoors

4.2.1 Species identification

Komi et al. (2007) combined spatial information from a low-cost RGB camera with spectral data from a line scan spectral camera (400-1000 nm) to classify the detached leaves of six plant species under halogen lighting with a shaded enclosure. Whilst LEDs provide monochromatic light, halogen lamps provide a continuous spectrum of light from visible to near-infrared wavelengths, thereby making it a suitable illuminator for spectral measurements.

4.2.2 Plant material identification

Applications of machine vision of plant structures include robotic harvesting of fruit in greenhouses. A differential two-waveband infrared vision system was designed and tested that made use of the spectral differences in fruit and leaves at 850 and 970 nm wavelengths to identify cucumbers on a vine (van Henten et al., 2002). This spectral difference also occurs between stems and leaves (Kondo & Ting, 1998). Additional image analysis enabled selective harvesting of only ripe or mature fruit by modeling the fruit size or volume.

Noordam et al. (2005) presented a comparison of a variety of methods for locating a cutting position on a rose stem, for the purpose of automation in the cut flowers industry. One of the methods evaluated was X-ray imaging and it was demonstrated that thin leaves were completely invisible in X-ray images. However, the approach was limited by stems occluding other stems and by the severe safety regulations of X-ray usage.

4.2.3 Stress detection
Potential multispectral imaging technologies for detecting plant water stress include visible, IR, NIR, UV and microwave radiation (Takakura et al., 2002). Bacci et al. (1998) showed that in a growth chamber, colorimetric techniques could be used to detect plant stress and Chaerle et al. (2003) used time-lapse thermal, fluorescence and video imaging of leaves to detect herbicide damage.

4.3 Discussion
Multispectral imaging provides information about properties of plants that are not visible to humans. The techniques potentially discern stress level or plant materials without requiring complex image analysis algorithms to replicate a human's visual appraisal of plant appearance. However, the expense of systems such as X-ray, tunable filters and thermal cameras restricts their application on-farm. Low-cost cameras are potentially sensitive to the visible and near infrared regions of the electromagnetic spectrum. Therefore, the addition of narrowband illumination or interference filters to a low-cost vision system has potential to accentuate plant features of interest at discriminatory wavelengths.

5. Range sensing
Range sensors are commonly 'active' sensor systems in which illumination is supplied as part of the system. The sensing systems are more robust to variations in ambient lighting than 'passive' sensor systems comprising only cameras. Similar to the visual hull method (Shlyakhter et al., 2001) using multiple camera images, range sensing provides information about the canopy bounding geometry.

5.1 Outdoors

Range sensing is typically used for generating maps of overall canopy size at high spatial resolution in the field. Geiger (2004) used an array of infrared emitters on either side of a cotton row to measure cotton plant height on-the-go. Tumbo et al. (2002), Wei & Salyani (2004) and Schumann & Zaman (2005) all used laser scanning and/or ultrasound to estimate the volume of trees in a citrus orchard.

5.2 Indoors

Range sensing using active sensor systems is not typically used indoors for measurement of living plants or canopies. This suggests that the technique is principally employed as a robust means of acquiring overall canopy geometry in the field environment and that a ‘passive’ camera-based system is sufficient or superior in controlled indoor environments for making equivalent measurements.

5.3 Discussion

Active sensing systems are effective for generating overall canopy dimensions without requiring complex stereo matching algorithms. However, at present, the method’s ability to provide more detailed information about canopy architecture appears limited.

6. Lighting design considerations for outdoor machine vision of plants

It is widely recognised (e.g. Slaughter et al., 2008) that machine vision systems for field use need to be designed to be robust to sunlight variations. As noted above, active sensing systems are less susceptible to ambient sunlight than passive sensing systems. However, low-cost (passive sensor) cameras with simple imposed illumination may also have reduced-dependency on sunlight (e.g. Edan et al., 2000).

Images collected by a camera do not need to look appealing to a human, but be in a format which simplifies processing for the computer (Harding, 2003). It follows that the imaging environment should be conditioned where possible to enable reliable and repeatable accentuation of the features of interest, which is desirable for automatic software algorithms.

In practical, application-driven research, prototype development is most rapidly expedited by concurrent design of the imaging apparatus and the image analysis algorithm/s. The following components have been identified from the preceding literature review as potential methods of enhancing machine vision system robustness in the field, particularly with respect to use of cameras:

- Shade structures mounted on on-the-go vision systems potentially inhibit movement of the system, particularly in mature canopies. Small, early-stage plants may potentially be completely enshrouded (e.g. Edan et al., 2000; Hemming & Rath, 2002). However, shading is necessary only to enable the artificial illumination scheme to be dominant (i.e. complete elimination of external lighting may not be required).

- Colour/reflectance reference panels presented in every image and under the same illumination condition as the imaged plant area may provide a constant reference of colour which potentially enables colour comparison under varying sunlight (e.g. Noh et al., 2005).
- Differential narrowband imaging provides spectral information with a dynamic spectral reference so that discrimination based on absolute reflectance thresholds can be reduced. For example, robust discrimination under varying lighting may potentially be achieved if imaging occurs simultaneously at a discriminatory wavelength (i.e. a band where the plant materials exhibit different spectral properties) and at a reference wavelength (e.g. a band where the plant materials exhibit similar spectral properties) (e.g. van Henten et al., 2002). Standard silicon-based camera technology provides NIR sensitivity up to approximately 1000 nm wavelength when the infrared-cut filter is removed. Narrowband imaging may potentially be achieved using narrowband optical filters or illumination (e.g. Carter & Miller, 1994).
- Artificial illumination applied intuitively to a scene potentially enables accentuation of shape properties, e.g. by use of silhouettes (e.g. Zeng et al., 2008) or by structured lighting (e.g. Waksman & Rosenfeld 1997; Noordam et al., 2005).
- Use of a mechanical agitator (e.g. an air stream or non-destructive contact with the foliage) potentially enables vision of parts of a plant that may be occluded by other foliage under static conditions (e.g. Hemming et al., 2005). Plant movement implies rapid image acquisition to 'freeze' the motion, but the standard video frame rate of 25 Hz is usually adequate. However, plant contact inherently reduces the speed at which the system can operate and increases the bulk of the mechanical structure in the field (e.g. McCarthy et al., 2009).
- Other technologies such as stereoimaging (e.g. Jin & Tang, 2009) and multispectral sensors (e.g. X-ray in Haff & Slaughter, 2009 and hyperspectral in Safren et al., 2007), potentially provide information that could augment a camera system.

Robust performance of the machine vision system may enable integration of the system with an existing farm operation. For example, attaching a machine vision system to the gantry of a centre pivot or lateral move irrigation machine potentially enables crop condition to be measured in real-time as the irrigation machine moves across the field (e.g. Colaizzi et al., 2003; McCarthy et al., 2009). Alternatively, tractor-mounting of the system may be desirable so assessments can be made as the tractor moves alongside the field. In this case, the sensed data may potentially be used to generate a map of plant attributes for use in informing management decisions.

7. Conclusions

On-the-go infield sensing of geometric crop plant parameters is currently limited to leaf shape identification and biomass estimation in the foliage of small plants, or plant height and biomass estimation in fully developed canopies. The desire to measure plant leaf-level attributes (e.g. internode length and leaf shape) in maturing field plants requires the design of a robust outdoor machine vision system that achieves detailed structure sensing. These systems have so far only been reported for automated laboratory or greenhouse systems on a limited number of crops under controlled lighting and environmental conditions. The literature to date indicates that achieving robust machine vision solutions in the field environment may require intuitive lighting and optical design earlier in the development of the system. Certainly, robust operation is required for the machine vision system to be used routinely in farming operations.

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