Determination of plant height for weed detection in stereoscopic images

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Abstract

The aim of this study was twofold. The first goal was to acquire high accuracy stereoscopic images of small-scale field scenes, the second to examine the potential of plant height as a discriminant factor between crop and weed, within carrot rows. Emphasis was put on how to determine actual plant height taking into account the variable distance from camera to ground and ground irregularities for in-field measurements. Multispectral stereoscopic images were taken over a period of 19 days starting one week after crop emergence and seven weed species were considered. Images were acquired with a mobile vision system consisting in a filter wheel based multispectral camera and a video projector. The stereoscopy technique used belonged to the coded structured light family.

The stereoscopic acquisition method yielded good results despite the numerous stereoscopic difficulties exhibited by the scenes. A plant height parameter as opposed to distance from camera to plant pixels gave better results for classification (classification accuracy of up to 83% for plant height parameter and 66% for distance from camera to plants).

Introduction

Pesticide use reduction is among the major challenges of agriculture. Mechanical destruction of weeds between rows of crops (whether guided by a human operator or by a computer vision system) is nowadays a common practice. However mechanical weeding inside the row (Figure 1) remains a time and money consuming manual operation for many horticultural crops. The development of an automated in-row weeding device for organic agriculture requires a precise localisation of weeds. Early weeding is particularly beneficial for carrots: some common annual weeds have their peak of germination around the same times as crop sowing and affect the crop growth (Turner and Davies, 2005). It has been shown that there is a significant effect of weed removal timing on the yield of carrots: 3-week and the 5-week weeded plots have a significantly greater yield than 7-week treatment (Turner and Grundy, 2002). Furthermore, carrots are sown in a relatively dense irregular pattern.

Figure 1. Examples of young carrot and weed plants on a ridge

In this paper, we first describe an acquisition method for high accuracy stereoscopic images of small scale agricultural scenes. Secondly, the acquired images are studied with regard to determining plant height to discriminate between crop and weeds.

Stereoscopic images of plants have been studied for various purposes: Several studies have used stereoscopic images to detect weeds. Nielsen and Andersen (2004) studied the detection of weeds among tomato plants by analyzing stereoscopic images acquired in field by a trinocular camera. The distinction between crop and weeds was based on three different methods: simple per-pixel threshold on distance from camera to plant pixels, analysis of connected blobs' height histograms and analysis of those same blobs after watershed segmentation. Authors acknowledge the negative effect of ground irregularity (seed line indentation) on classification. Sanchez and Marchant (2000) briefly described the possibility of detecting weeds by a fixed threshold on plant height on stereoscopic images of plants in laboratory conditions. The stereoscopic images were acquired by a depth from motion technique. Other plants' properties have also been studied on stereoscopic images. Andersen et al. (2005) studied the possibility of computing geometric plant properties such as plant height and leaf area on stereoscopic images acquired with a binocular camera, on potted plants. They showed that those characteristic can be accurately determined using stereovision. He et al. (2003) used stereoscopic images acquired by a binocular camera to successfully evaluate plant height and leaf area, among other parameters, on transplants. Moeslund et al. (2005) determined the pose of cactus leaves on binocular stereoscopic images acquired using plant specific features to compute the correspondence on binocular stereoscopic images. Mizuno et al. (2007) studied the detection of wilt in plants. For plants with sparse leaves they used a binocular camera to acquire stereoscopic images and determine leaves' angles relative to the plant. With regards to the difficulty of acquiring good quality stereoscopic data of plants, Nielsen et al. (2007) developed a framework to compare and tune stereoscopic algorithms on virtual images of various plants. A similar approach was used by Reng et al. (2003). Chapron et al. (1993) pointed out the efficiency of incorporating knowledge about plants' structures into the stereoscopic algorithms when studying 3D reconstruction of corn plants by two stereoscopic algorithms on binocular images.

Stereoscopic imaging aims to record three-dimensional information. There are mainly two kinds of acquisition methods: passive and active. Passive methods usually rely on several views of the same scene to recover depth information (e.g. binocular stereoscopy, similar to human depth perception). Active methods are characterized by the projection on the scene of some form of energy (commonly light) to help acquire depth information. We refer the reader to Jarvis (1993) for an in-depth analysis of range data acquisition. Binocular stereoscopy is pretty common since it is simple to implement in hardware and is well suited to real-time acquisition. However, robust acquisition of dense stereoscopic data by this technique is not an easy task.

Since the object of this study was not real time acquisition of stereoscopic images but the study of those images, and that several problems were encountered for passive stereoscopic data acquisition of the scenes (numerous occlusions, repetitive texture areas, texture-free areas, high dynamic range, reflective surfaces and thin objects high dynamic range, repetitive texture areas, lowly textured areas, thin objects and occlusions), it was chosen to use an active system, based on coded structured light. This technique is based on the projection of light on the scene to make the correspondence problem easier. Its principle is to project a single or multiple light patterns on the scene, for example with a video projector. In the pattern or group of patterns, the position of each element (line, column, pixel or group of pixel) is encoded (Figure 3). The information extracted by active stereovision is usually of better precision and higher density than the one obtained using binocular stereoscopy techniques. There are numerous coded structured light approaches. A recent review of those strategies can be found in Salvi et al. (2004).

The distance of the plants relative to the measurement device is not a good indicator of their actual heights if the distance from the device to the ground varies or if the ground is irregular, especially if the plants are young and therefore of small size, which is the case for this study. We thus aimed at computing a height parameter independent of those problems and to use this parameter to discriminate between crop and weeds.

Materials and methods

Image acquisition

The main requirement for the coded structured light stereoscopic imaging system was to integrate the existing multispectral camera used in this study to allow registration of height information over multispectral images. The multispectral camera was based on a black and white camera (C-cam BCI 5 1.3 megapixels) coupled with a filter wheel holding 22 interference filters covering the VIS-NIR spectral domain. A more thorough description of the multispectral part of the acquisition and data analysis can be found in Piron et al., 2008. It was thus chosen to use a single camera based structured light approach that consists of the aforementioned multispectral camera and a DLP video projector (OPTOMA EP719 with a 1024x768 resolution). Acquisition speed and mechanical vibrations concerns due to the filter wheel dictated the use of monochromatic patterns acquired without filter in front of the camera. A mobile support frame was designed to allow acquisition of top-down images of the field scene (approximately 200 by 250 mm, see Figure 2).

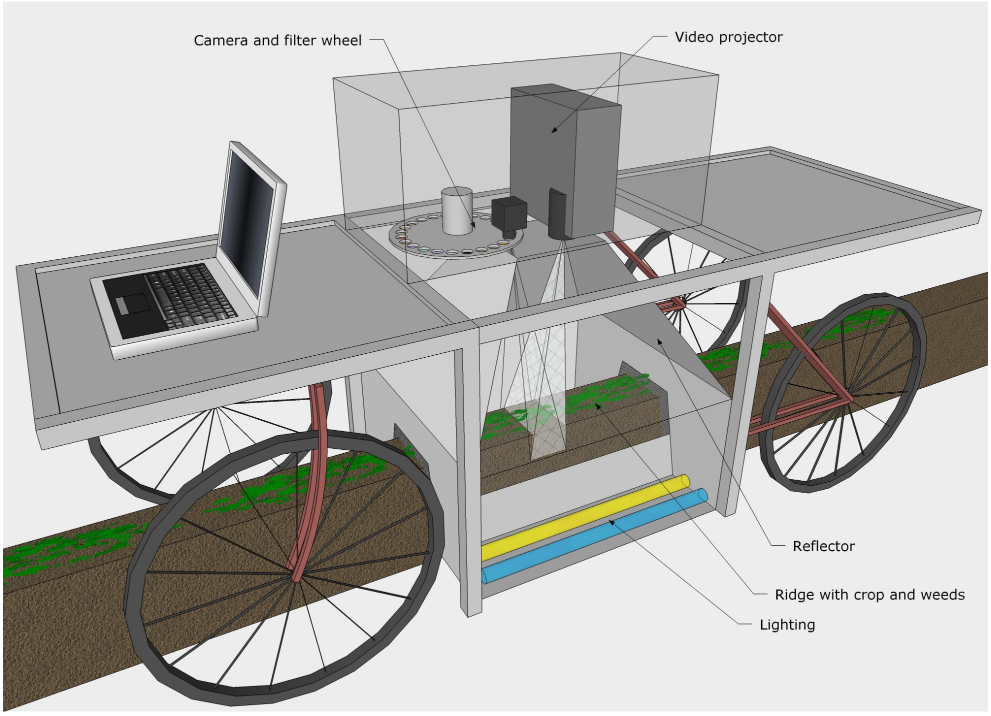

Figure 2. Mobile support frame for the multispectral stereoscopic camera

The coded structured light technique developed had to take into account the specificities of the small scale agricultural scenes, namely occlusion and thin objects, internal reflections and scene high dynamic range. It was also necessary to obtain robust results and take into account the specificities of the video projector.

Table 1 summarizes the choice of the codification and strategies used to overcome those problems. Since fast acquisition was not a concern and a black and white camera was used (for the multispectral part of the acquisition device), we decided to use a time multiplexing approach with a binary codeword basis (black or white illumination).

Table 1. Summary of the difficulties for stereoscopic acquisition of small-scale in-field plants

Problem	*Solution*
Presence of occlusions, thin objects	Per pixel decoding
Shallow projector depth of field	Per pixel decoding, weakly correlated codes
High dynamic range	High dynamic range acquisition, correlation based decoding
Internal reflections	Pseudorandom pattern

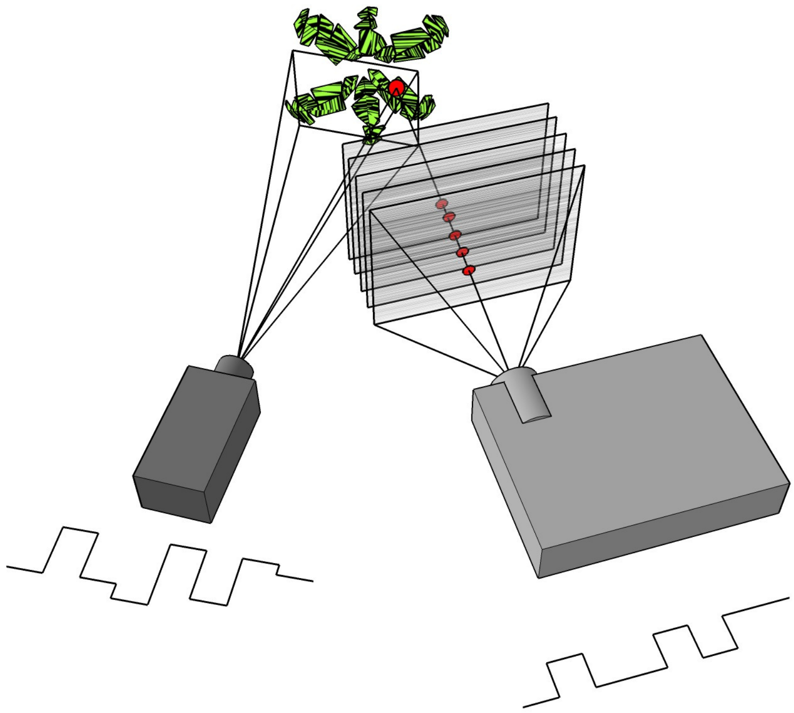

Figure 3. Principle of time multiplexing coded structured light, camera on the left, video projector on the right.

Because of the large amount of occlusions and thin objects (such as plant bracts), we chose to use a per pixel decoding scheme, where code is decoded at every camera pixel rather than using neighbour pixels.

The nature of the code was chosen to give robust results in presence of high dynamic range scenes, which pose problem for many existing techniques (Wu et al. 2006). We used weakly correlated codes with a minimum Hamming distance[1] of 8 (empirically determined). The length of the code used was 22 bits, which allowed for the minimum Hamming distance requirement and gave good decoding results. The codes were decoded by correlation: the signal received by a single camera pixel over time was compared with all possible signals. As correlation also gives a measure of the reliability of the decoding, it was used to remove spurious measurements by applying a threshold.

Usually, in time multiplexing binary or gray code techniques, the projected images are comprised of black and white bands of large then finer width. The wider bands cause problems when the scene is prone to internal reflections (the illuminated part one part of the

[1] The Hamming distance between two codes is the number of corresponding bits that are different

scene will illuminate other parts of the scene) the. The code used here also happened to be pseudorandom (i.e. no apparent structure) which resulted in a more uniform illumination.

The scenes presented a high dynamic range since the reflectance of soil can vary greatly with its moisture content and certain plant species had a highly reflective surface. We thus chose to acquire high dynamic range images using multiple exposures blending. Four exposures of each pattern were taken at different exposure times and linearly blended. The number of exposure and the exposure times were determined empirically on potted plants. The high dynamic range acquisition allowed us to have a strong signal to noise ratio for all pixels of the image.

An equipment related problem encountered was the shallow depth of field of the projector: given the size of the scene and distance from projector it was not possible to have the projected pattern sharp on close and distant object of the scene. The choice of a per-pixel decoding scheme combined with the weakly correlated code was also motivated by that characteristic.

The calibration of the camera-projector system was done using the Zhang technique from the Intel OpenCV library.

Study site and acquired data

The study concerned two carrots' varieties without distinction, Nerac F1 and Namur F1, sown on 27-04-06 in an experimental field in Gembloux (Belgium). Approximately 200 linear metres of rows were mechanically sown at a density of 10 to 15 seeds per 100 mm long by 50 mm wide which is a common commercial planting density. Several species of weeds were naturally present in the field and others were manually introduced. The main species were the following at the time of data acquisition: Sonchus asper L., Chenopodium sp., Achenocloa sp., Cirsium sp., Merurialis M. perennis, Brassica sp. and Matricaria maritima. Other species might have been present. Weeds were considered as a single class in the discrimination approach since they appeared in fields in unpredictable species and quantities. Table 2 gives a summary of acquired data. Images were acquired at an early growth stage of both carrots and weeds (from one week after crop emergence to 19 days later which is the usual period for manual weeds removal). Indeed, early weed detection can increase yields and weed elimination becomes increasingly difficult with plant growth. In May, the soil was wet and dark, while it was dry and brighter in June. A total of 28 multispectral stereoscopic images were acquired at random locations in the parcel. The number of images acquired per day varied according to meteorological conditions: strong winds made the acquisition of stereoscopic images difficult because of the movement of plants and/or camera.

Table 2. Summary of acquired data.

Date of data acquisition	*Days after sowing*	*Soil surface state*	*Acquired stereoscopic multispectral images*
22-05-06	21	Wet	4
29-05-06	28	Wet	4
31-05-06	30	Wet	9
07-06-06	37	Dry	7
09-06-06	39	Dry	4

Stereoscopic data classification

The second goal of this study was to use plant height as a discriminant parameter between crop and weed. The raw data acquired by the stereoscopic device was not plant height but the distance of the plants relative to the measurement device. This distance doesn't accurately represent plant height if the position of the device relative to the ground varies or if the ground is irregular. We thus computed a new parameter called corrected plant height which is independent of those problems by using plant and ground data. This parameter is the distance between plant pixels and the actual ground level under them obtained by fitting a surface and seen from a reconstructed point of view corresponding to a camera's optical axis perpendicular to the ridge plane.

The whole process is described in Figure 4: First we segmented plant and ground pixels in the images using only the multispectral data (1, 2). This operation was done on two spectral bands by quadratic discriminant analysis (Piron et al., 2008). Then, we fitted two surfaces through the soil pixels, one plane (3) and one triangle-based cubic interpolated surface (4), using the griddata function of Matlab.

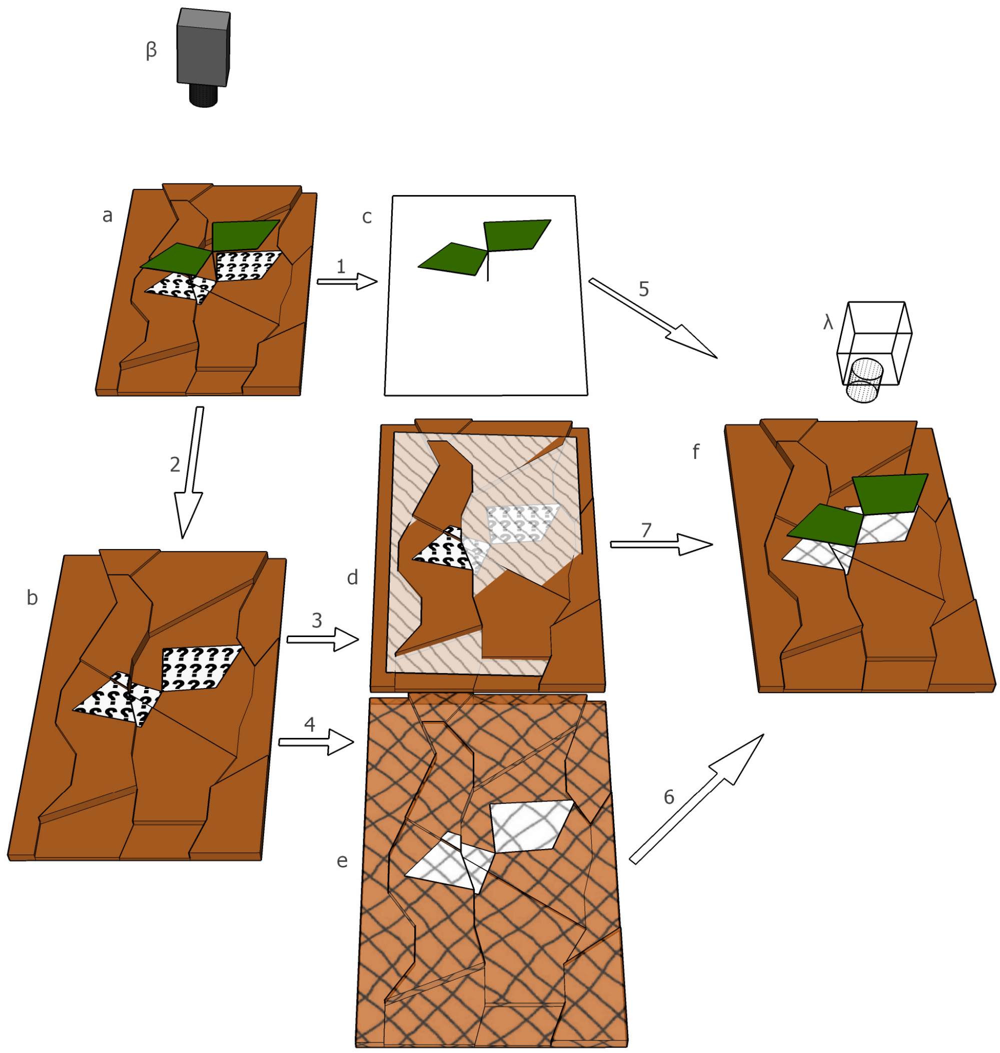

Figure 4. Process for determining plant height parameter

The plant and soil pixels (the latter with the interpolated pixels obtained in operation 4 since the ground under the plants was not visible from the camera, and not all points seen by the camera were illuminated by the projector) were then put back together (5,6). Finally, the orientation of the fitted plane was used to rotate the data in space as to align the plane normal with a virtual camera (λ) optical axis.

For the classification (by means of a quadratic discriminant analysis), we used two parameters. The first parameter is for each plant pixel the distance between the plant pixel and the reconstructed soil underneath (corrected plant height). The second is the number of days after sowing, which allowed taking into account the various growth stages of the plants.

Results and discussion

Stereoscopic image acquisition

The stereoscopic data acquisition gave highly detailed images with dense stereo data and few decoding errors, as can be seen in Figure 5 despite the numerous problems contained in the scene or arising from the material.

The structures of plants with finely dissected leaves such as *Matricaria maritima* are clearly visible. The great variability in height of the ground can also be seen in those examples.

Figure 5. Crops of stereoscopic images

Stereoscopic data classification

For plant classification, it was found that the measurement device position and ground irregularities greatly influenced the classification accuracies and that using the corrected plant height, which took into account a correction for those effects, improved the classification results (Table 3).

The overall classification accuracy without correction was of 66%. For the corrected height parameter, the overall classification accuracy was 83%.

For the carrot class alone, there was a smaller improvement when going from the non corrected height parameter to the corrected plant height than for the weed class. This can be explained by the central position of the carrot plants on the ridge and the better surface state of the soil in that area of the ridges, due to the sowing apparatus.

Table 3 – Classification results

		Parameter	
		Non corrected plant height	*Corrected plant height*
Classification accuracy (%)	*Overall*	66	83
	Carrots	75	85
	Weeds	57	80

Conclusion

A coded structured light method suited for acquiring high quality stereoscopic images of small scale field scenes was described. The data acquisition was carried out in field conditions, over a period of 19 days, starting one week after crop emergence. During this period, the presence of weeds has the most negative effect on yield. Seven different weed species were considered.

A method for determining actual plant pixel height was developed. This method took into account the irregularities of the ground and the variable location of the acquisition device due to in field conditions. The method showed a greatly increased classification accuracy compared to the used of uncorrected distance from camera (from 66 to 83%).

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