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IN-FIELD CROP ROW STEREO-RECONSTRUCTION FOR PLANT PHENOTYPING

Sylvain JAY¹, Gilles RABATEL¹, Nathalie GORRETTA¹

¹UMR ITAP, Irstea, 361 rue J.F. Breton, Montpellier, France

Abstract. This article presents a methodology for crop row structure characterization developed for phenotyping purpose. It is based on 3D modeling performed using Structure from Motion. The model provides an accurate crop row reconstruction and serves as a basis to retrieve plant height and leaf area. To do so, a robust discrimination method using both color and height information is proposed to separate vegetation from soil. The point cloud is scaled and the plant surface is approximated by a triangular mesh. The efficiency of our method was assessed with two data sets collected in outdoor conditions. Height estimation was extremely accurate since both average error and error of reference measurement had the same order of magnitude. Strong correlations and low errors were also obtained for leaf area estimation. The proposed method thus provides an interesting tool for phenotyping.

Keywords: In-field phenotyping, 3D modeling, Structure from motion, Plant/soil discrimination, Plant height retrieval, Leaf area retrieval.

1 Introduction

In a context of a greener and more competitive agriculture, developing efficient phenotyping methods has become a topic of major interest for plant breeding. Numerous parameters have to be retrieved, especially those characterizing the plant structure, such as height or leaf area.

3D reconstruction performed by stereovision-based methods has proven to be an interesting way to retrieve these structural parameters. In controlled indoor conditions, many solutions have been proposed (Bellasio et al., 2012; Thiago Santos, 2012; He et al., 2002; Chéné et al., 2012), but unfortunately, most of them are not adapted to phenotyping (low throughput, dedicated to a single variety, ineffective under natural light). In outdoor conditions, the reconstruction process and estimation results can be substantially affected by various phenomena such as wind or heterogeneous background and lighting. As a matter of fact, only few authors conducted field studies (Kise and Zhang, 2008; Leemans et al., 2012). To deal with such conditions, Lati et al. (2013) have recently proposed a novel approach for the estimation of height, leaf cover area and biomass volume. Their method can even handle occluded areas to some extent (i.e. overlapped leaves).

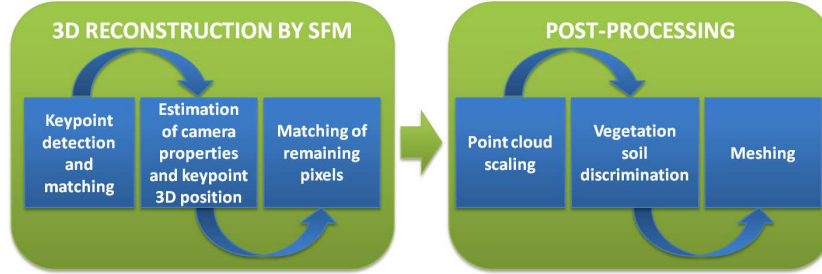


Fig. 1: Framework of the proposed method.

Such 3D-based measurements often necessitate to discriminate plant from background, since only plant-related information is used to retrieve structural parameters. Most usual discrimination methods involve thresholding a vegetation index map obtained from RGB bands (Meyer and Neto, 2008). On the other hand, Lati et al. (2013) used a hue-invariant transformation that is robust under natural lighting. However, like every other color-based discrimination method, this approach fails if the contrast between plants and soil is low, which makes their 3D-based measurement method ineffective in such cases.

This study proposes a 3D modeling based methodology to characterize crop rows in outdoor conditions (i.e. to retrieve structure, plant height and leaf area). Special attention is given to the methodology robustness against heterogeneous lighting and low vegetation/soil contrast. Moreover, other phenotyping-related needs (non-destructive, automatic, fast) are considered. We use Structure from Motion (SfM) to obtain the crop row 3D model, whereas most authors usually used classical stereovision. Structural parameters are then retrieved from this model.

This paper is organized as follows. Section 2 presents the proposed approach. The data sets as well as some details about the implementation of the method are described in Section 3. Section 4 shows the results of 3D reconstruction, discrimination and growth parameter retrieval. Lastly, Section 5 draws some conclusions.

2 Proposed approach

The framework of the proposed method is presented in Fig. 1. A first part is related to the 3D reconstruction performed using SfM. In a second part, various post-processing steps are applied to the 3D model in order to retrieve the growth parameters of interest.

2.1 3D reconstruction

Stereovision allows to retrieve object 3D structure from 2D images acquired from different view angles. Using SfM, these view angles are obtained by moving a

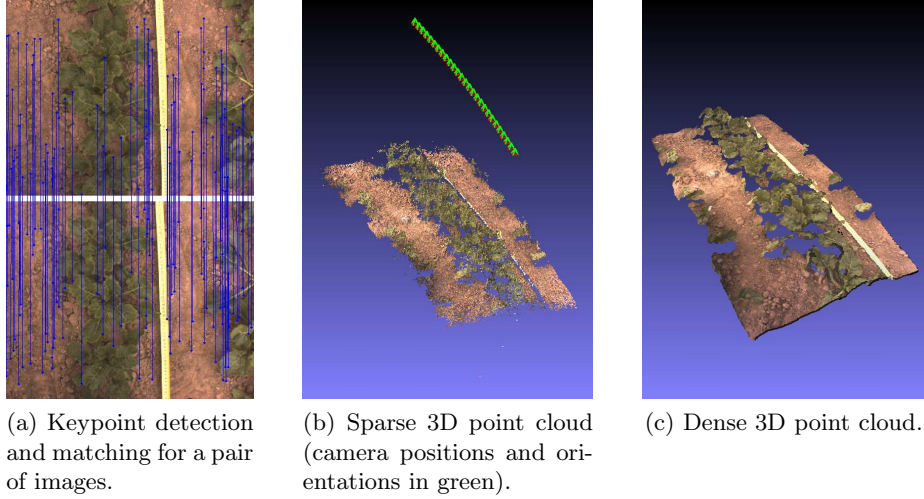


Fig. 2: 3D reconstruction steps.

single camera round the object of interest. This motion is either unconstrained or constrained by a translation stage. In this latter case, the camera is translated at a given speed and acquires an image at every Δx , where Δx is the baseline. Therefore, every point of the scene is seen in several images that correspond to several view angles. Knowing the position of a given point in several images and successive camera positions, the point position can be estimated by ray intersection. An advantage of using SfM compared with classical stereovision is that it does not need any prior camera calibration. Indeed, the high number of images and use of a unique camera allow to simultaneously estimate camera properties and 3D model.

The three usual main steps of SfM are described in the following paragraphs. The first step consists in retrieving and matching similar feature points that are seen in two overlapping images using the scale-invariant feature transform (SIFT) (Lowe, 2004). This method has been designed to provide keypoint descriptors that are invariant to scale, rotation, translation and exposure. Examples of such extracted keypoints obtained for a couple of images are shown in Fig. 2a. In the second step, these keypoints are used as inputs of an iterative algorithm that simultaneously estimates their 3D position and the camera internal calibration, position and orientation for every image. At each iteration, an image is added and a bundle adjustment is performed in order to limit error accumulation (Hartley and Zisserman, 2004). The computed sparse point cloud (corresponding to keypoint positions) and the camera successive positions are presented in Fig. 2b.

Lastly, in the third step, a dense point cloud is produced from estimated orientations and positions of the camera. For this purpose, a matching process using

cross-correlation is implemented. For a given pair of overlapping images, a pixel in the first image is associated with the pixel that is located on the epipolar line in the second image and that maximizes the cross-correlation criterion. This operation is repeated for every couple of images so that the estimated position of considered point is less sensitive to noise. An example of crop row reconstruction is shown in Fig. 2c.

2.2 Post-processing

Once the crop row structure has been modeled, various additional processing steps have to be implemented in order to retrieve growth parameters from the 3D model.

First, the point cloud has to be given an appropriate scale that allows to retrieve height and area values in SI units (resp. cm and cm²).

Then, an important step is to discriminate soil-related pixels from plant-related pixels, since only the latter is used to estimate height and leaf area. In order to increase the class separability obtained when using only color information, we propose to take into account spatial information as well, and use together the height H and Excess Green Index (ExG) (Woebbecke et al., 1995). Indeed, the higher the point, the more likely it belongs to the vegetation class. To do so, after having estimated the crop row structure, we perform discrimination using a clustering algorithm with two classes (vegetation and background). Plant height is finally retrieved by computing the difference between the plant highest height and the mean ground height.

Concerning leaf area, an additional post-processing step is needed in order to reconstruct the plant surface. A triangular mesh is produced from the point cloud and the leaf area is then approximated by summing every polygon area.

3 Materials and methods

3.1 Data

We assessed the efficiency of our method with two data sets collected in outdoor conditions. Different sensors, acquisition means, lighting conditions and crop row structures were considered.

The first data set comprised images acquired with a digital single-lens reflex (DSLR) camera (Canon 500D). Four plant species or varieties were imaged in order to deal with different plant structures: sunflowers (*Helianthus annuus*), Savoy cabbages (*Brassica oleracea* var. *sabauda*), cauliflowers (*Brassica oleracea* var. *botrytis*) and Brussels sprouts (*Brassica oleracea* var. *gemmifera*). The camera was looking towards nadir and images were acquired approximately every 10 cm by manually moving the camera at about 1 m above the ground level (depending on plant height).

The second data set was collected in sugar beet (*Beta Vulgaris*) fields in Vimy

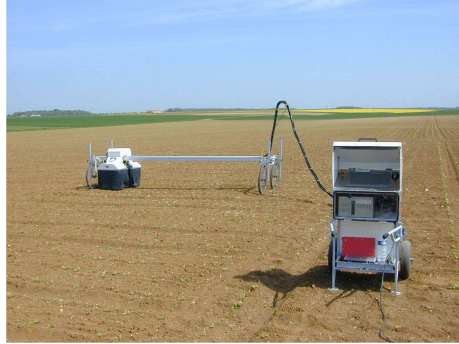


Fig. 3: Becam phenotyping platform.

Table 1: Height (H) and leaf area (LA) ranges for the two data sets (min-max).

	Data set 1				Data set 2
	Sunflower	Savoy cabbage	Cauliflower	Brussels sprout	Sugar beet
H (cm)	15-65	10-17	19.5-22.5	11.5-17.5	×
LA (cm ²)	27-1201	99-331	360-538	80-573	378-622

(northern France) within the framework of AKER project¹. Two sugar beet varieties subjected to four different nitrogen applications were imaged. To do so, a digital CCD camera was mounted on the translation stage of the Becam phenotyping platform² (Benet and Humbert, 2009) (see Fig. 3). The camera was looking towards nadir at 1.20 m above the ground level and acquired images every 4 cm along the crop row so that every point in the scene was imaged from a dozen view angles.

For both data sets, a tape measure was disposed into the scene before acquiring images. This allows to scale the 3D model and obtain measurements in centimeters and square centimeters.

Reference height measurement was performed manually by measuring the distance between the mean ground level and the plant highest point. To perform reference leaf area measurement, limbs were harvested, disposed on blank sheets and flattened with a pane of glass before scanning. Leaf-related pixels were then extracted by image processing. Finally, leaf area in cm² was obtained from leaf area in pixels using pixel size calibration. In the second data set, only one mean measurement of leaf area (carried out on four to six plants) was available for each row.

Height and leaf area ranges for the two data sets are reported in Tab. 1.

¹ AKER is a project funded by the French National Research Agency and partly devoted to sugar beet phenotyping

² The Becam phenotyping platform was developed by Irstea for plant counting and belongs to the French Sugar Beet Technical Institute (ITB).

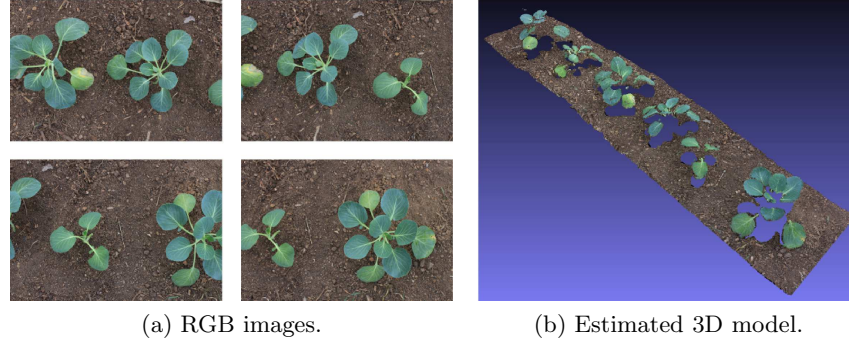


Fig. 4: Savoy cabbage row reconstruction performed with 38 images.

3.2 Implementation

Regarding 3D reconstruction, SfM was implemented with MicMac, a digital surface model freeware developed by IGN (2007). Section 2.1 only describes an overview of the main steps performed by MicMac. For more information, the reader can refer to the associated documentation (IGN, 2007).

Regarding post-processing steps, scaling was done thanks to a reference object disposed in the scene (see the yellow tape measure in Fig. 2). Discrimination was performed using H and ExG with the k-means (KM) clustering algorithm (Lloyd, 1982) implemented with two classes. Lastly, plant surface was approximated using the ball-pivoting algorithm (Bernardini et al., 1999) implemented in Meshlab.

In order to assess height and leaf area estimation results, we used the coefficient of determination (R^2), root mean square error (RMSE) and mean absolute error (MAE). In particular, RMSE and MAE have been defined by Willmott and Matsuura (2005).

4 Results and discussion

4.1 3D reconstruction

An example of reconstruction built from the first data set is presented in Fig. 4 (Savoy cabbages). Sugar beet row reconstruction obtained from the second data set is shown in Fig. 2c. In every case, SfM gave an accurate crop row 3D model. Moreover, this method was robust against acquisition means and sensor quality, which were different within the two data sets. In the first data set, the translation motion was performed manually, moving the camera horizontally above the ground level. As a result, the camera altitude, view angle and baseline between two successive positions differed from an image to another. However, this does not affect the reconstruction process, which makes the method flexible and easy to implement (no need for a specific imaging setup).

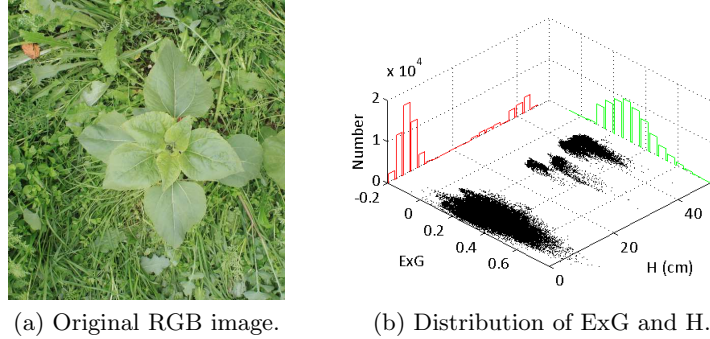


Fig. 5: Example of low-contrasted scene.

In the second data set, good reconstruction results were obtained even though the sensor quality was lower.

Reconstruction was performed with a 3.60 GHz processor and 4 GB of RAM. Overall processing time was comprised between 30 seconds and 60 seconds per image, depending on the crop row structure complexity and the number of images.

4.2 Discrimination vegetation/soil

The interest of using height for discrimination is illustrated in Fig. 5. In the RGB image shown in Fig. 5a, both sunflower and background have similar ExG values. Moreover, the background is heterogeneous so the ExG range is wide (between 0 and 0.8). In this case, color is not a relevant parameter to discriminate both classes since there is only one mode on the green histogram in Fig. 5b. On the other hand, at least two distinct modes are seen on the red histogram showing the height distribution. In fact, there are one main cluster for the background and one or more clusters for the plant. This scatter plot shows that height information can remove ambiguity occurring when using color only.

4.3 Plant height estimation

Fig. 6 shows the results of height estimation performed on the first data set. Estimated values are plotted against actual values for every studied species.

We obtained a strong linear correlation and low average errors between estimated and actual values ($R^2 = 0.99$, RMSE = 1.1 cm, MAE = 0.85 cm). RMSE and measurement error (due to rough ground, moving leaves, etc) had the same order of magnitude, which demonstrates that crop row 3D models give extremely accurate estimates of plant height. Moreover, Fig. 6 shows that the proposed method obtained similar R^2 , RMSE and MAE for every species, thus proving that the method can handle various crop structures.

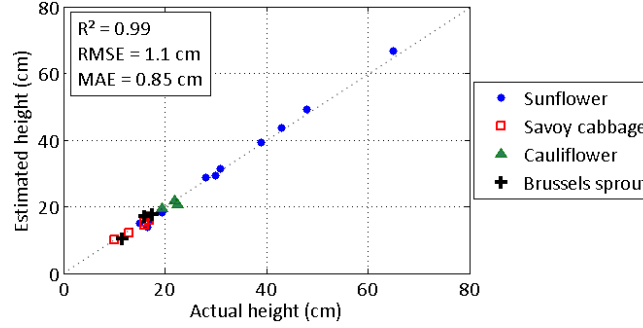


Fig. 6: Height estimation results obtained with the first data set.

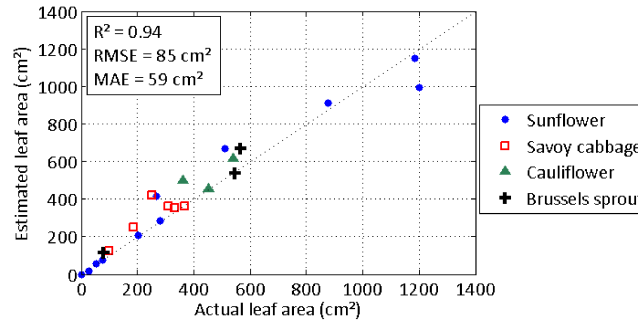


Fig. 7: Leaf area estimation results obtained with the first data set.

4.4 Leaf area estimation

For the first data set, in Fig. 7, estimated leaf areas are plotted against actual leaf areas for every species. We also obtained a strong linear correlation and low average errors between estimated and actual values ($R^2 = 0.94$, $RMSE = 85 \text{ cm}^2$, $MAE = 59 \text{ cm}^2$). It shows the potential of our method for leaf area estimation in outdoor conditions. Estimation results were good for every single species. Relative MAE were 12% for sunflower and Brussels sprout, 16% for cauliflower, and 21% for Savoy cabbage. These figures prove that performance remained stable for the considered plant structures.

For the second data set, leaf area estimation results are shown in Fig. 8. For each row, the actual mean value is compared with the mean value estimated with the proposed approach. Sample means and standard deviations (shown with error bars) were computed from four to six plants.

The estimated mean leaf areas were close to the actual mean leaf areas. Indeed, RMSE and MAE computed with these mean values were 66 cm^2 and 45 cm^2 respectively (i.e. 13% and 9% resp.). The actual mean leaf areas were in the intervals specified by sample standard deviations except for row 6. In this latter

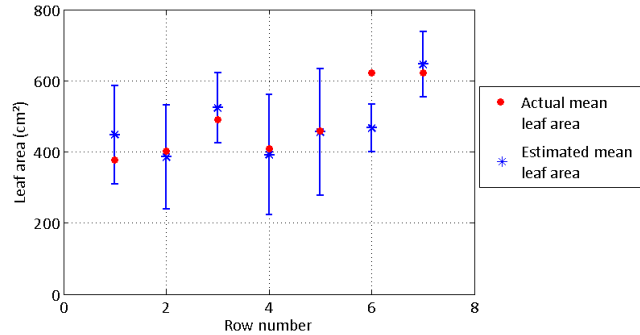


Fig. 8: Leaf area estimation results obtained with the second data set. The errors bars are the sample standards deviations computed from four to six plants.

case, results were probably less accurate because of many overlapped leaves that were not handled by the proposed method.

5 Conclusions

This study presents a methodology to retrieve crop row 3D structure, plant height and leaf area. It has been designed in order to fulfill phenotyping-related needs to some extent (non-destructive, automatic, robust, fast). The crop row 3D structure is retrieved by SfM using images acquired by a single moving camera. Various post-processing methods are then implemented to estimate plant height and leaf area. In particular, we propose a plant/soil discrimination method that is robust in outdoor conditions. This method provided good results for various crop structures, lighting conditions, sensors and image acquisition means.

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References

Bellasio, C., Olejníčková, J., Tesar, R., Sebel, D., Nedbal, L.: Computer reconstruction of plant growth and chlorophyll fluorescence emission in three spatial dimensions. *Sensors* 12, 1052–1071 (2012)

- Benet, B., Humbert, T.: Realisation du systeme Becam portique pour l'acquisition d'images sur deux raies de betteraves. Technical Report, Cemagref (2009)
- Bernardini, F., Mittleman, J., Rushmeier, H., Silva, C., Taubin, G.: The ball-pivoting algorithm for surface reconstruction. *IEEE Transactions on Visualization and Computer Graphics* 5, 349–359 (1999)
- Chéné, Y., Rousseau, D., Lucidarme, P., Bertheloot, J., Caffier, V., Morel, P., Belin, E., Chapeau-Blondeau, F.: On the use of depth camera for 3D phenotyping of entire plants. *Computers and Electronics in Agriculture* 82, 122–127 (2012)
- Hartley, R.I., Zisserman, A.: *Multiple View Geometry in Computer Vision*. Second ed., Cambridge University Press (2004)
- He, D., Hirafuji, M., Kozai, T.: Growth prediction of a transplant population using artificial neural networks combined with image analysis. In: *Third Asian Conference for Information Technology in Agriculture*, pp. 266–271 (2002)
- IGN: Micmac. URL: <http://www.micmac.ign.fr/> (2007)
- Kise, M., Zhang, Q.: Development of a stereovision sensing system for 3D crop row structure mapping and tractor guidance. *Biosystems Engineering* 101, 191 – 198 (2008)
- Lati, R.N., Filin, S., Eizenberg, H.: Estimating plant growth parameters using an energy minimization-based stereovision model. *Computers and Electronics in Agriculture* 98, 260–271 (2013)
- Leemans, V., Dumont, B., Destain, M.F., Vancutsem, F., Bodson, B.: A method for plant leaf area measurement by using stereo vision. In: *CIGR-AgEng 2012 International Conference on Agricultural Engineering* (2012)
- Lloyd, S.: Least square quantization in pcm. *IEEE Transactions on Information Theory* 28, 129–137 (1982)
- Lowe, D.G.: Distinctive images features from scale-invariant keypoints. *International Journal of Computer Vision* 60, 91–110 (2004)
- Meshlab, URL: <http://meshlab.sourceforge.net/>
- Meyer, G., Neto, J.: Verification of color vegetation indices for automated crop imaging applications. *Computers and Electronics in Agriculture* 63, 282–293 (2008)
- Thiago Santos, A.O.: Image-based 3d digitizing for plant architecture analysis and phenotyping. In: *Workshop on Industry Applications (WGARI) in SIB-GRAPI 2012 (XXV Conference on Graphics, Patterns and Images)*, pp. 21–28 (2012)
- Willmott, C.J., Matsuura, K.: Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. *Climate Research* 30, 79–82 (2005)
- Woebbecke, D.M., Meyer, G.E., Barga, K.V., Mortensen, D.A.: Color indices for weed identification under various soil, residue, and lighting conditions. *Transactions of the ASAE* 38, 259–269 (1995)