3D LEAF TRACKING FOR PLANT GROWTH MONITORING

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ABSTRACT

This article presents a 3D approach in plant growth monitoring and deals with the tracking of leaves of sunflower plants. Our aim is to compute time-series of individual leaf area, under water stress and control conditions. These data will then be used by biologists to study the drought resistance of various sunflower species. Our method to track the leaves in 3D has been evaluated on a set of 132 point clouds obtained via classical structure-from-motion techniques and multi-view stereo software. These 3D acquisitions have been performed on 12 sunflower plants (6 water-stressed, 6 well-watered) during a period of one month (11 measurement dates per sunflower plant). This method gives promising results for both conditions (water-stressed and well-watered), for different species and is able to follow the growth of the plants, as well as to detect new leaf emergence and leaf decay.

Index Terms— 3D leaf tracking, plant monitoring, time tracking, labelling, 3D plant phenotyping, Sunflower plants.

1. INTRODUCTION

In order to increase food production through improved crop performance, research in plant breeding focus on relationships between genotype (DNA) and phenotype (visual characteristics). While genotyping methods are rapidly improving, most of the current phenotyping methods are manual, invasive and sometimes destructive. In order to fill the gap between genotype and phenotype data, phenotyping was recently linked with automation and signal processing to increase its throughput [1, 2]. Aiming to study drought resistance of sunflower plants, a key plant's characteristic under a changing climate, the French National Institute for Agricultural Research has developed a semi-controlled outdoor phenotyping platform allowing agronomists and geneticists to monitor up to 1300 plants in pots and control the water stress of each plant.

Recent studies pointed the use of 3D data in order to automatically extract visual characteristics of a plant instead of 2D images because the main limitations in 2D come from occlusions due to overlappings between leaves [3, 4, 5]. In 3D the problem still persist but few examples have shown that the use of Structure from Motion is well adapted in 3D plant digitalization and reconstruction and can be used for 3D plant phenotyping [4, 5]. We previously addressed 3D reconstruction and 3D model-based segmentation in [6, 7] (1) to obtain a 3D model of a plant and (2) to extract the stem, and to segment, label and compute the area of every leaf.

The problem addressed here, monitor the leaves during the plant growth, reveals a great challenge in following a live object in 3D like a sunflower plant, that grow in an unpredictable way and remains a major problem in plant phenotyping. To meet this challenge, we work on plant growth in pot in a semi-controlled outdoor phenotyping platform. The starting point of our labelling method is a 3D point cloud of a sunflower plant already segmented. We start by isolating a plant and take about hundred images around it, under controlled light illumination and wind condition. Then we use classical structure from motion techniques and multi-view stereo software like OpenMVG [8] and PMVS/CMVS [9, 10] in order to reconstruct the plant in 3D [6]. After cleaning the point cloud, we apply a stem extraction algorithm in order to ease the leaves segmentation by using an Euclidean cluster extraction as detailed in [7].

This paper is focused on the leaves tracking during the plant growth, it introduces a labelling method that allows to track the leaves over times. It is organized as follows: section 2 presents our method to track the leaves during the plant growth. Section 3 shows the results obtained on a set of 12 sunflower plants during a period of one month and finally, section 4 draws conclusions on the use of this method and provides guidelines for further works.

2. METHOD

As our main objective is to follow the expansion rate of leaf areas on sunflower plants during their growth, we have turned the problem into a 3D object tracking over time, applied to track the leaves. To reach this aim, we have developed a method with (1) an initial labelling step relying on the botanical model of a sunflower plant that allows to assign a unique label to each leaf, (2) a label propagation step that allows to track the leaves, making sure that these labels do not change
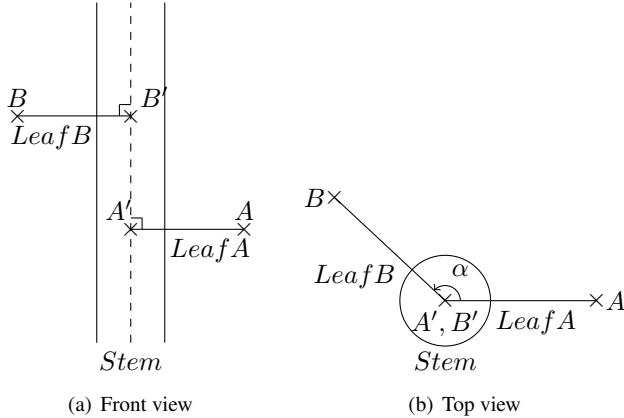
(a) Front view   (b) Top view

Fig. 1. Description of divergence angle computation

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Algorithm 1: Initial leaves labelling
   input  : Leaves
   output : Leaves labelled
 1 // Sort the leaves by the height of their insertion point
 2 sort (leaves);
 3 foreach (leaf in leaves) do
 4     nextLeaf ← leaf.next;
 5     thirdLeaf ← nextLeaf.next;
 6     if (nextLeaf.height ≃ thirdLeaf.height) then
 7         α₁ = divergenceAngle(leaf, nextLeaf);
 8         α₂ =
            divergenceAngle(leaf, thirdLeaf);
 9         if (α₂ − 137.5° < α₁ − 137.5°) then
10             swap (nextLeaf, thirdLeaf);
11         end
12     end
13 end
```

over time, and (3) the detection of new leaf emergence and of old leaf decay.

We will present how we design our labelling method to follow leaves over time, introducing the sunflower phyllotaxy, that describes the way how leaves appear and are organised along the stem. First, we will detail the initial labelling step used to assign a unique label to every leaf, and then the propagation step used to follow leaves over time.

2.1. Leaves labelling

2.1.1. Plant phyllotaxy

The main function attributed to phyllotaxy is to increase the ability of the plant to intercept light for photosynthesis by minimizing cast shadows between leaf layers. The arrangement of leaves appears as regular and is the result of biochemical control during the leaf appearance and expansion. The emergence of leaves respects particular rules proper to each specie. Two types of phyllotaxy are observed: cyclic and spiral ones. If there is only one leaf per node (term used to express where leaves appear on the stem), it is a spiral arrangement, if there are two leaves or more per node, it is a cyclic arrangement as explained in [11, 12]. In the cyclic phyllotaxy, the leaves at each node form a whorl with constant angles between leaves. In a spiral leaf arrangement, a single leaf is attached to a particular node on the stem, leaves are distributed around the stem in a spiral pattern. A plant with a spiral arrangement consistently has a symmetrical pattern with the exact same number of leaves for each turn around the stem. The angle between two successive leaves around the stem is called, **divergence angle**. It represents how a new leaf on the plant stem is positioned with respect to the previous one. This divergence angle is always constant but differ between species [13].

In sunflower plants, two types of phyllotaxy were identified, depending on the leaf position on the stem: the first three pairs of leaves are organized with a cyclic phyllotaxy (*oppo-

site decussate*, successive leaf pairs are $90°$ apart), while from the leaf 7, it appears a spiral phyllotaxy with an angle of divergence $\alpha = 137.5°$. The first pairs decay quickly in favour of the ones arranged in spiral [14].

2.1.2. Initial leaves labelling

Knowing that the main sunflower phyllotaxy is spiral, *i.e.*, there are only one leaf per node, the first idea was to sort the leaves by the height of their insertion point along the stem and to assign them a label according to this order. The leaf at the bottom will receive the label 0, the next one, the label 1 and so on. Moreover, knowing that the theoritical divergence angle for a sunflower plant is $\alpha = 137.5°$, we used it in order to detect potential labelling errors. The divergence angles are always computed in the counter-clockwise direction as shown in Figure 1 and with the following equation:

$$\alpha = \begin{cases} \arccos(\vec{L_A} \cdot \vec{L_B}) & \text{if } det(\vec{L_A}, \vec{L_B}) \geq 0 \\ 360 - \arccos(\vec{L_A} \cdot \vec{L_B}) & \text{otherwise} \end{cases} \quad (1)$$

where $\vec{L_A}$ & $\vec{L_B}$ means $LeafA$ & $LeafB$ and the determinant $det(\vec{L_A}, \vec{L_B})$ is used to detect the angle orientation. In [6] we have shown that this divergence angle might not respect the model when two leaves have close insertion points on the stem. If it is the case, labels of these two leaves need to be swapped in order to get a divergence angle that respects the model.

All these observations have lead to the Algorithm 1, which is used as an initial labelling step for each sunflower plant. The next step, is to verify these labels by propagating the ones obtained at the previous acquisition, checking and correcting them in order to ensure that every leaf keeps the same label during the plant growth period.

Algorithm 2: Labels propagation

> **input** : Previous divergence angles
> **output:** First label

1    $sumAngle \leftarrow 0$;
2   **foreach** *(angle in previousDivergenceAngle)* **do**
3       $sumAngle \leftarrow sumAngle + angle$;
4   //Check $angle$ modulo (2π)
5   **if** *($\alpha_{ref} - sumAngle < -toleranceAngle$)* **then**
6         $\alpha_{ref} \leftarrow \alpha_{ref} + 360$;
7   **end**
8   //Compare $angle$
9   **if** *($\left|sumAngle - \alpha_{ref}\right| < toleranceAngle$)* **then**
10   Correspondance found;
11   **end**
12 **end**

2.2. Labels propagation

Our main objective is to monitor the plant growth, usually during a month. We perform a 3D acquisition every 2, 3 or 4 days and apply our initial leaves labelling algorithm to each plant from its 3D reconstruction. During the monitoring process, we always take care to perform the acquisition with the same plant orientation. We compute the divergence angle of the first leaf with the x-axis in order to get the orientation of the plant. We call this angle, the referential divergence angle (α_{ref}). Here the main problem comes from the growth of the plant itself, as our labelling method relies on the height of the leaf insertion points on the stem. Knowing that the inter-node distance grows uncertainly depending on the plant environment (light illumination, water, temperature...), it is possible that two leaves close at a certain time, are distant from each other at another time, making their label switched. Moreover, the first leaves can decay and disappear and new leaf can appear in an unexpected way.

In order to detect and address these kind of events, we propagate the labels obtained at the previous acquisition (except for the initial acquisition where there is no previous label). First, we have developed the Algorithm 2 in order to compare the referential divergence angle with the one obtained at the previous acquisition to retrieve the label of the first leaf, as well as to detect potential leaf decay. Then, we compare the other divergence angles in order to check if no label have been switched. The divergence angles are compared with a certain tolerance to be invariant against uncertainty and noise related to the 3D reconstruction and segmentation.

3. RESULTS

In order to evaluate the accuracy and repeatability of our method, we have performed a test on a set of 12 sunflower plants from 2 different species, 6 plants have been placed under water stress condition and 6 under control condition (well-watered). The test was performed during autumn 2017, between the beginning of September till mid-November with 3D aquisitions made every 2, 3 or 4 days for a total of 11 acquisitions per plant and a full amount of 132 point clouds of sunflower plants. An example of 3D plant growth monitoring is given in Figure 2, where we can see that the leaves keep the same labels during the monitoring period[1].

3.1. Segmentation

As the starting point of our method is a 3D sunflower plant, where the leaves have already been segmented, we present the segmentation results obtained on a set of 132 point clouds. In most cases, plants have been successfully segmented, only 4 point clouds have not been well segmented, which represents 3% of faillure. Moreover, these failure only appears for the plants at an advanced stage of water stress. For each well segmented plant, 80% of the leaves have been retrieved and the 20% missing are the small leaves that are appearing under the top of the plant (the *capitulum*), but as shown in [6], we assumed that the smaller leaves (under the top) do not contribute strongly to light interception and plant functioning and so, are not considered in the phenotyping method.

3.2. Initial leaves labelling

For the initial leaves labelling step, due to the particular phyllotaxy of the sunflower plant (opposite phyllotaxy following by a spiral one), if the leaves that appear in pairs are still present when we start the acquisition, it is difficult to determine which leaf is the first. In order to solve this issue, we execute the Algorithm 1 twice, swapping the label of the two first leaves between the execution. This gives two configurations and we have to select the one that respect the phyllotaxy of a sunflower plant. An example is given in the table 1 where it is possible to see the result associated to the acquisition made during the first date *Day 1*. Here, the first iteration gives the best solution. This method was able to label all the segmented leaves in our set of 132 point clouds, for the 2 species and in both conditions (water-stressed and well-watered).

3.3. Labels propagation

The aim of the labels propagations step is two-fold: (1) propagate the previous label in order to find the correct label of the first leaf as well as to detect potential leaf decay and (2), check that all the divergence angles are in accordance with the previous ones in order to make sure that labels have not changed.

In order to illustrate the problem of leaf decay, we present in Table 2 results obtained for a plant where two leaves have

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[1]This paper has supplementary examples provided by the authors. It includes two videos showing the monitoring of a stressed and a well irrigated plant during their growth. This material is 12.7 MB in size.
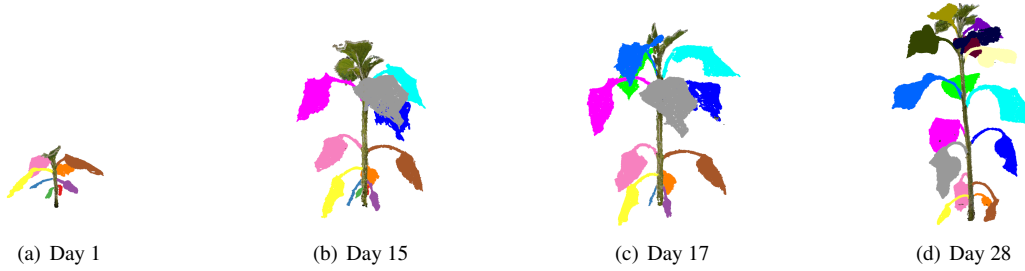
(a) Day 1   (b) Day 15   (c) Day 17   (d) Day 28

Fig. 2. Plant growth monitoring

First iteration			Second iteration		
Labels	Angle	Model	Labels	Angle	Model
(0-1)	183.3°	180°	(0-1)	176.65°	180°
(1-2)	91.5°	90°	(1-2)	88.3°	90°
(2-3)	173.4°	180°	(2-3)	186.5°	180°
(3-4)	111.7°	90°	(3-4)	77.7°	90°
(4-5)	152.6°	137.5°	(4-5)	207.3°	180°
(5-6)	125.8°	137.5°	(5-6)	278.4°	180°
...	...	...	...	...	...

Table 1. Example of initial leaves labelling at *Day 1*

	Day 15	Day 17	
Labels	Angle	Angle	Observation
α_{ref}	134.6°	53.5°	-
$\alpha_{(0-1)}$	195.7°	-	Decay
$\alpha_{(1-2)}$	83.2°	-	Decay
$\alpha_{(2-3)}$	158.6°	164.4°	√
$\alpha_{(3-4)}$	111.7°	110.2°	√
...	...	...	...
$\alpha_{(11-12)}$	-	124.5°	New leaf
$\alpha_{(12-13)}$	-	149.9°	New leaf

Table 2. Example of labels propagation

decayed 17 days after the first acquisition. In this table, we present the divergence angle available at the previous acquisition: *Day 15*. On *Day 17*, we have a referential divergence angle between the first leaf and the x-axis $\alpha_{ref_{(17)}} = 51.3°$. We can retrieve the label associated to this leaf by comparing $\alpha_{ref_{(17)}}$ with $\alpha_{ref_{(15)}}$ and all the divergence angles on this day. In this case:

$$\alpha_{ref_{(17)}} \simeq \alpha_{ref_{(15)}} + \alpha_{(0-1)_{(15)}} + \alpha_{(1-2)_{(15)}} \quad (2)$$
$$= 134.6° + 195.7° + 83.2° = 413.5° \quad (3)$$
$$= 53.5° (2\pi). \quad (4)$$

We can see that two leaves present at *Day 15* (Figure 2(b)) have decayed and are no longer present at *Day 17* (Figure 2(c)), which means that the label of the first leaf available at this date is no longer 0 but 2. Our method works for our point clouds but has a limitation due to the use of a referential divergence angle (α_{ref}) computed between the first leaf and the x-axis, plants have to be placed in the same orientation for the 3D acquisition during the monitoring period. In our dataset of 12 sunflower plants, the leaf decays appear at different times according to the specie but the method was able to detect them.

4. CONCLUSION

In this paper we have presented a 3D approach for plant growth monitoring applied to sunflower plants. This approach relies on our previous work made on 3D plant reconstruction and segmentation that was validated on sunflower and sorghum plants [6, 7]. The idea is to follow the plant growth of sunflower plants and especially, to follow the leaves over time. To do so, a labelling method has been developed relying on the phyllotaxy of sunflower plants. This method allows us to (1), follow each leaf individually by assigning a unique label that does not change over time and (2), to detect new leaf emergence and old leaf decay during the plant growth. This method was tested on a set of 12 plants with 11 acquisitions associated to each plant during a period of one month and has been proven to be robust enough to follow the leaves during the plant growth. After being able to follow the leaves during the plant growth, more work will be focused on computing leaves characteristics (*e.g.*, area, color, curvature with the stem, etc), with the specific aim to determine if a leaf is still active or not. Here, the challenge might be solved by machine or deep learning, by training the system with annotated agronomist data.

6. REFERENCES

[1] Stijn Dhondt, Nathalie Wuyts, and Dirk Inzé, "Cell to whole-plant phenotyping: the best is yet to come," *Trends in Plant Science*, vol. 18, no. 8, pp. 428–439, 2013.

[2] Fabio Fiorani and Ulrich Schurr, "Future Scenarios for Plant Phenotyping," *Annual review of plant biology*, vol. 64, pp. 267–291, 2013.

[3] Gaëtan Louarn, Serge Carré, Frédéric Boudon, Annie Eprinchard, and Didier Combes, "Characterization of whole plant leaf area properties using laser scanner point clouds," in *Fourth International Symposium on Plant Growth Modeling, Simulation, Visualization and Applications*, 2012.

[4] T. T. Santos and A. A. Oliveira, "Image-based 3D digitizing for plant architecture analysis and phenotyping," in *Workshop on Industry Applications (WGARI)*, 2012.

[5] Sylvain Jay, Gilles Rabatel, Xavier Hadoux, Daniel Moura, and Nathalie Gorretta, "In-field crop row phenotyping from 3D modeling performed using Structure from Motion," *Computers and Electronics in Agriculture*, vol. 110, pp. 70–77, 2015.

[6] William Gélard, Michel Devy, Ariane Herbulot, and Philippe Burger, "Model-based Segmentation of 3D Point Clouds for Phenotyping Sunflower Plants," in *Proceedings of the 12th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications*, 2017, pp. 459–467.

[7] William Gélard, Ariane Herbulot, Michel Devy, Philippe Debaeke, Ryan F. McCormick, Sandra K. Truong, and John Mullet, "Leaves Segmentation in 3D Point Cloud," in *Advanced Concepts for Intelligent Vision Systems*. 2017, pp. 664–674, Springer International Publishing.

[8] Pierre Moulon, Pascal Monasse, Romuald Perrot, and Renaud Marlet, "OpenMVG: Open Multiple View Geometry," in *Reproducible Research in Pattern Recognition*. 2017, Springer International Publishing.

[9] Yasutaka Furukawa, Brian Curless, Steven M. Seitz, and Richard Szeliski, "Towards Internet-scale Multi-view Stereo," in *CVPR*, 2010.

[10] Yasutaka Furukawa and Jean Ponce, "Accurate, Dense, and Robust Multi-View Stereopsis," *IEEE Trans. on Pattern Analysis and Machine Intelligence*, vol. 32, no. 8, pp. 362–1376, 2010.

[11] Samuel Boissìere, "Dynamique de la Phyllotaxie," 2000.

[12] Chrystel Feller, Christian Mazza, and Florence Yerly, "Plantes, spirales et nombre : les plantes font-elles des maths?," *Bulletin de la Société Fribourgeoise des Sciences Naturelles*, vol. 99, pp. 122–137, 2010.

[13] Soumendra Kumar, "Phyllotaxy (Arrangement of Leaves): Cyclic and Spinal Phyllotaxy," .

[14] Hervé Rey, Jean Dauzat, Karine Chenu, Jean-François Barczi, Guillermo A. A. Dosio, and Jérémie Lecoeur, "Using a 3-D Virtual Sunflower to Simulate Light Capture at Organ, Plant and Plot Levels: Contribution of Organ Interception, Impact of Heliotropism and Analysis of Genotypic Differences," *Ann Bot*, vol. 101, no. 8, pp. 1139–1151, 2008.