Model-based Segmentation of 3D Point Clouds for Phenotyping Sunflower Plants

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Keywords: 3D Plant Phenotyping, Structure from Motion, Clustering, Labeling, Nurbs Fitting, Sunflowers.

Abstract: This article presents a model-based segmentation method applied to 3D data acquired on sunflower plants. Our objective is the quantification of the plant growth using observations made automatically from sensors moved around plants. Here, acquisitions are made on isolated plants: a 3D point cloud is computed using Structure from Motion with RGB images acquired all around a plant. Then the proposed method is applied in order to segment and label the plant leaves, i.e. to split up the point cloud in regions corresponding to plant organs: stem, petioles, and leaves. Every leaf is then reconstructed with NURBS and its area is computed from the triangular mesh. Our segmentation method is validated comparing these areas with the ones measured manually using a planimeter: it is shown that differences between automatic and manual measurements are less than 10%. The present results open interesting perspectives in direction of high-throughput sunflower phenotyping.

1 INTRODUCTION

Thanks to the rapid development of high throughput genotyping methods during the last decade, plant scientists have now access to a huge amount of data on genome sequences and genes with new avenues for increasing production and secure food demand. With the perspective of a sustainable agriculture and issues raised by climate change, a better understanding of relationships between genotype (DNA) and phenotype (visual characteristics) in a given environment became the main issue in agricultural research (Dhondt et al., 2013; Fiorani and Schurr, 2013). Currently, most plant phenotyping methods are manual, invasive, sometimes destructive, do not allow to obtain high throughput results and slow down the research.

The French National Institute for Agricultural Research (**INRA**) is working on the Sunrise project, a joint research program on sunflower adaptation to drought in Toulouse at the interface of ecophysiology and genetics. To fill the gap of phenotyping, a platform has been built, allowing to monitor up to 1300 sunflower pots and control the water stress of each plant. This paper puts the emphasis on the development of tools that allow to characterize from 3D data acquired on isolated plants, information for each leaf, making possible a temporal analysis of leaf expansion and senescence of sunflower plants.

In this study, a model-based segmentation of 3D point clouds acquired on isolated sunflower plants, is proposed with an attention given on the labeling of each leaf in order to be able to compute leaf area dynamics. The following terms will be used in this article (see figure 1):

- Main stem, the primary plant axis that starts from the soil (here in a pot) and supports the leaves.
- Leaf: an unstructured thin and more or less elongated object, the area of the upper (adaxial) side must be estimated from 3D points assigned to its surface.
- Petiole: a thin stalk from the main stem to a leaf. The petioles insertion positions on the stem allow to label leaves: for all varieties of sunflower, a widely adopted rule for numbering the leaves is used so that each leaf is given a unique label.
- Top: the crown of the plant, at the stem extremity, where young leaves appear around the capitulum. Leaf area is computed only when the leaf is more than 6cm long; the capitulum is not considered in computations.

Gelard W., Devy M., Herbulot A. and Burger P.
Model-based Segmentation of 3D Point Clouds for Phenotyping Sunflower Plants.
DOI: 10.5220/0006126404590467
In *Proceedings of the 12th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2017)*, pages 459-467
ISBN: 978-989-758-225-7

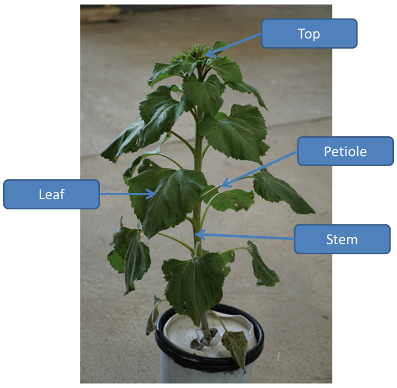

Figure 1: Description of a sunflower plant.

Biologists require an automatic method in order to characterize the plant state, typically the total plant leaf area, here computed by summing all the individual leaf areas. Moreover they are interested in monitoring the individual leaf expansion all along the vegetative phase and green leaf area decline after flowering to study dynamics of plant variables.

This paper is organized as follows: section 2 presents the acquisition method used to obtain a 3D point cloud on a sunflower plant, section 3 presents the different studies on 3D plant phenotyping, section 4 presents the proposed method for the model-based segmentation of a 3D point cloud, providing the reconstruction of each leaf. Section 5 shows the results with a comparison of the computed leaves areas with the manually acquired ground truth. Finally, the section 6 draws conclusions on the use of this method for sunflowers phenotyping and provides guidelines for further works.

2 3D ACQUISITION ON THE PLANT

Our first aim was to find a way to obtain the leaf area of a whole sunflower plant with a non-destructive, non-invasive and automated method. To do that, recent studies trend towards the use of 3D data (Louarn et al., 2012; Santos and Oliveira, 2012; Lou et al., 2014; Jay et al., 2015). By now, what emerges from those papers is that the 3D model of a plant could be exploited for 3D plant phenotyping, i.e. for the estimation of the main parameter of our phenotyping problem which is the leaf area.

The problem looks into which kind of sensors or techniques could be used to acquire a 3D model of a sunflower. Like presented in (Paulus et al., 2014), since few years, a multitude of sensors and technologies have seen the day, like Time of Flight (ToF) camera, laser scanner, depth camera, stereovision, etc. Some of those sensors are expensive and do not really increase the performance for our kind of application. Moreover, like presented in (Santos and Oliveira, 2012) the use of low cost sensors like single hand-held cameras combine with Structure from Motion (SfM) technique are well adapted for plant digitizing. In this way, the work made in (Quan et al., 2007) allows to obtain a 3D model from a single hand-held camera based on the work of (Lhuillier and Quan, 2005); it built a fully 3D point cloud for a poinsettia plant but required the interaction of a user in order to combine 3D and 2D informations with an eye to segment leaves and to reconstruct them. So in order to avoid user interaction, and with the recent progress in Structure from Motion, the effort made to obtain a 3D model of a sunflower was concentrated on the usage of Bundler (Snavely et al., 2006), a Structure from Motion system applied on unordered image collections. This system takes as input a set of images taken around the plant and provides a sparse point cloud. Then a dense point cloud is provided from the CMVS (Furukawa et al., 2010) and PMVS2 (Furukawa and Ponce, 2010) software, a multi-view stereo software (MVS) that takes as input the spare point cloud produced by Bundler. Moreover, during the acquisition process, a chessboard pattern is placed on the ground in order to retrieve the scale of the cloud. Outliers are manually removed with Meshlab and the cloud is then scaled with CloudCompare.

An example of a 3D point cloud acquired on a sunflower with Bundler+CMVS/PMVS after the filtering and scaling steps, is given in figure 2. As visible in this figure, the 3D point cloud gives a faithful reconstruction of the sunflower. The resolution could be yet increased by taking advantage of other packages like Micmac, used in (Jay et al., 2015) but less user friendly. Another solution is to use commercial packages, like Agisoft PhotoScan, which allows to acquire denser and more accurate 3D point clouds, but it increases the overall cost of the workflow.

Figure 2: 3D point cloud given by Bundler+CMVS/PMVS.

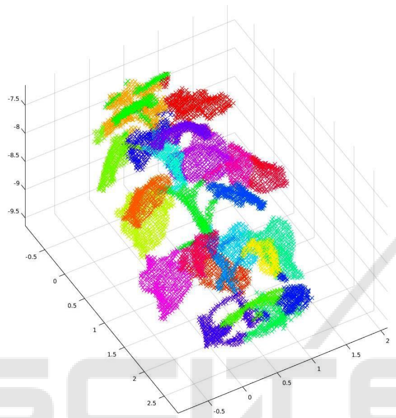

Figure 3: Result of K-means algorithm with k=25.

3 RELATED WORK ON PLANT SEGMENTATION

Once the 3D model of a plant is acquired, different parameters need to be extracted. To do that, it is important to separate each part of a plant, namely, the main stem, each leaf and the top. In (Santos et al., 2015), it was shown that it is possible to separate the main stem from leaves by using a spectral clustering algorithm (Ng et al., 2002). The problem is that the number of clusters must be given as input, what requires the interaction of a user. In the same optic, the K-means algorithm (J. A. Hartigan, 1979) was tested and the result (see figure 3) was correct, except that the main stem was segmented in several parts and leaves under the top were merged with it.

With the aim to avoid user interaction, the DBSCAN algorithm (Ester et al., 1996), a density-based algorithm was tested. This algorithm can achieve the leaves segmentation without specifying the number of clusters. In general, this algorithm meets the same problem as K-means for the main stem and the top. Furthermore, the parameters required by this algorithm are quite a bit difficult to tune for a multitude of varieties. An example of result produced by this algorithm is shown in figure 4.

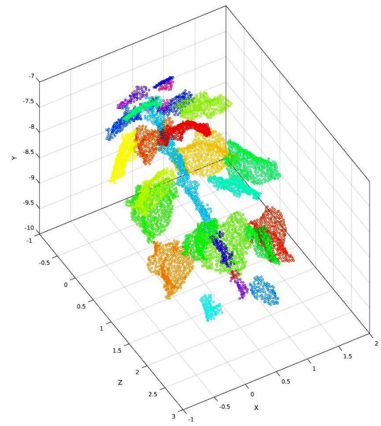

Figure 4: Result of DBSCAN algorithm.

Another approach consists in working with the 3D mesh built from the point cloud, like (Paproki et al., 2012). To obtain such a mesh of a plant, they use 3DSOM, a commercial 3D digitization software. They first apply a coarse segmentation with a constrained region-growing algorithm which allows to identity the main stem and leaves. Then, a tubular shape fitting provides a precise stem segmentation, the petioles, their inter-nodes and finally they proceed to the leaf segmentation. While this method requires a strong knowledge about the model of the plant; it allows to realize a temporal analysis but requires to build first a 3D mesh from the point cloud. Here, the problem is that it is very difficult to obtain the 3D mesh of the whole sunflower plant from the SfM results. We have evaluated several methods: a fast triangulation of unordered point clouds (Marton et al., 2009), poisson reconstruction (Kazhdan et al., 2006) and ball pivoting (Bernardini et al., 1999), but none of them gave exploitable results, probably due to the low resolution of the point cloud.

An alternative approach to address the issue of 3D plant segmentation was developed by (Paulus et al., 2013). The main idea making profit of the model of the plant, is that a plant is made up of leaves attached to a main stem. So the key issue was to find a way to pull apart those two clusters. Here the method was based on the use of Point Feature Histograms (PFH) descriptor (Rusu et al., 2009), that encodes a point's k-neighbourhood geometrical properties based on normal and curvature around the point. This descriptor was adapted into Surface Feature histograms (SFH) in order to make a better distinction between leaves and stem. This new kind of descriptor were used as features for a Support Vector Ma-

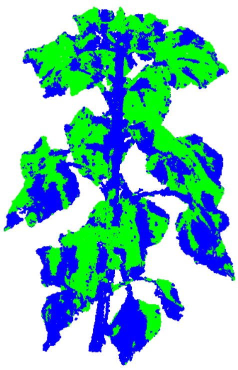

Figure 5: Result of K-means on SFH with K=2.

chine (SVM) classification, i.e. a supervised method that requires an a priori manual learning of the model. So a user is needed to manually label the point cloud and to give the machine what is a stem and what is a leaf. Triggered by the motivation of obtaining a fully automated method, (Wahabzada et al., 2015) also used the Surface Feature Histogram but used a K-means algorithm instead of SVM in order to segment those two clusters. This method works well with grapevine, wheat and barley and was tested with our sunflower point cloud. To achieve this, the implementation of PFH available in the Point Cloud Library (PCL) (Rusu and Cousins, 2011) (a great tool for 3D point cloud development) was adapted in order to obtain SFH. The implementation works pretty well but the specific shape of a sunflower leaf prevents us from segmenting the leaves and the main stem as presented in the figure 5. The problem is also due to the 3D point cloud itself, indeed, the 3D reconstruction is incomplete and some leaves have 3D points on each side whereas other ones have 3D points only on one side. The SFH computation requires the estimation of the normal and curvature on each 3D point from its neighbourhood; disparities between normals of neighbour points belonging to opposite sides of a leaf, lead on a bad segmentation.

So the main challenge for plant phenotyping is the segmentation process: like methods presented in section 3 do not allow us to segment a sunflower, our idea is to rely more on the knowledge of the sunflower model, like in (Paproki et al., 2012). This model is directly exploited during the segmentation process; the method is presented in the rest of this paper.

4 PROPOSED METHOD

The proposed method deals with the segmentation of a 3D point cloud acquired on a sunflower with Bundler+CMVS/PMVS, as explained in section 2. A sunflower is composed of a main stem, a top, leaves and petioles. We assumed that the smaller leaves (under 6cm of length) did not contribute strongly to light interception and plant functioning and were not considered in the phenotyping method.

The proposed model-based segmentation method aims mainly to obtain plant leaf area in an automatic way; each leaf must be individually extracted and reconstructed, so that its area can be computed. To achieve the leaf extraction, we have shown that the known segmentation method gave results that were not accurate enough for our application case. In order to simplify the problem, we first start by looking for the stem and we remove it from the cloud. It allows us to perform the leaf segmentation only based on a geometrical constraint. Then, we can find the petioles insertions of each leaf and used it to label the leaves according to the known botanical sunflower model. Finally, the leaves are reconstructed by NURBS fitting and their area are computed from the associated triangular mesh.
All the implementation was done in C++ with PCL.

4.1 Main Stem Extraction

Our first idea was to localize the main stem by a cylinder fitting and to remove all points located along this cylinder. The consequence of this is the filtering of all points belonging to the main stem, to the top, and to all leaves (and petioles) located above the top, which are the leaves that are under 6cm of width. To do that, we apply the procedure given in PCL (Rusu, 2009) in order to estimate parameters of a cylinder fitted to the main stem, i.e. the axis and the radius. We next locate all the points included in this cylinder and propagate them from the bottom of the 3D point cloud to the top. This method works well with straight stem but met some difficulties with curved stem, hence our more tricky method for the main stem extraction.

The second idea, we considered a ring with an a priori known radius (based on a botanical sunflower model) that starts from the bottom of the plant and climbs along the stem by using both a neighbourhood constraint as well as a normal constraint. Indeed, each point of the cloud produced by Bundler+CMVS/PMVS are defined by:

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- Coordinate (X,Y,Z)
- Colour (R,G,B)
- Normal direction (X,Y,Z)
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The normal direction of the points contained in the ring are used to compute the direction of the ring (along the stem), then, each point in the neighbourhood of this ring is tested and if its normal direction is perpendicular (with a certain flexibility) to the stem it

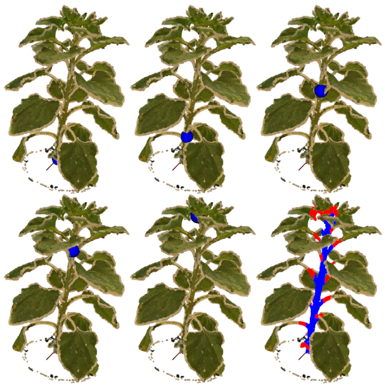

Figure 6: Example of the ring climbing along the stem.

Figure 7: Result of ECE on the petioles insertions cloud.

is added to the ring while the first ones are removed. The fusion of all rings climbing along the stem, defines a generalized cylinder, i.e. a ring with a fixed radius, moving along a curved axis.

4.2 Petioles Insertions on the Stem

The next step is the localisation of the petioles insertion points on the stem. Here the idea was to extend the radius of the ring that models the stem at a given heigth, defining a cylindrical crown, i.e. two generalized cylinders of same axis but with different radius. So a radius (called petioles_radius) is selected larger than the one used for the ring (called stem_radius). While the ring is climbing along the stem, the points located in the crown (between the stem_radius and the petioles_radius) are segmented as petioles insertions while the ones located in the ring are segmented as stem. In the figure 6, we can see in blue, the ring climbing along the stem and, bottom right, the fusion of all rings. We can also observe that some petioles insertions are labelled as stem; but this is not a problem because we only want to be able to remove the stem in order to exploit a geometrical constraint for the leaf extraction as explained hereafter.

4.3 Petioles Insertions Clustering and Labelling

We used the petioles insertions to segment and label each leaf individually. First a cloud only composed of the petioles insertions is extracted, and analysed by an Euclidean Cluster Extraction (ECE), a clustering method relying on a geometrical constraint as explained in (Rusu, 2009). A result is given in figure 7. Once we get these clusters, the botanical sunflower model is used to label them. Labels affected to each leaf rely both on their insertion order along the stem and their phyllotaxic angles, i.e. angles between two successive leaves, defining the arrangement of leaves around a plant stem. In sunflower, the first leaves have opposite orientations while the remaining consecutive leaves have relative orientations around 137° as described in (Rey et al., 2008). Table 1 presents the computed phyllotaxic angles and shows that the botanical model is well respected except for the leaves 11, 12 and 13 where the angles between the leaves 11 & 12 and 13 & 14 are around 90°. Nevertheless, we can see that the height insertion of the leaves 12 and 13 are very close (abs(0.346902-0.35354) = 0,006638m $\leq$ 1cm). If we switch the position of these two leaves and compute the new phyllotaxic angles we can observe that they better fit the model as shown in table 1. From this result, we have designed our method to only check the phyllotaxic angle between two leaves only if they are close and to correct the labeling only if it does not respect the model.

4.4 Leaf Segmentation

The next step consists in segmenting each leaf individually, starting from the 3D point cloud without stem. From that, we can perform a segmentation based on a geometrical constraint. Here, we also apply the Euclidean Cluster Extraction and the result of which is shown in figure 8. In this figure, it is possible to see that most of the leaves have been well segmented, except for a few of them on the top of the sunflower (however less than 6cm of length) and the label can be assigned from their petioles insertions. After that, and with the aim of compute only the leaf area, we have to separate the leaves from their petioles. Here, we also used a ring moving along the petiole but now, starting from the petiole insertion on the stem and stopping when it reaches the leaf as shown in figure 9.

Table 1: Phyllotaxic angles without label correction.

Leaves label	Height insertion (m)	Phyllotaxic angle (°)
1-2	(0.0169748-0.0301619)	174.024
2-3	(0.0301619-0.0560179)	109.427
3-4	(0.0560179-0.0847796)	148.132
4-5	(0.0847796-0.126075)	131.256
5-6	(0.126075-0.155893)	137.634
6-7	(0.155893-0.190812)	125.147
7-8	(0.190812-0.205754)	153.823
8-9	(0.205754-0.249005)	117.355
9-10	(0.249005-0.268278)	146.015
10-11	(0.268278-0.288003)	141.211
11-12	(0.288003-0.346902)	**87.3252**
12-13	(**(0.346902-0.35354)**)	133.72
13-14	(0.35354-0.392951)	**95.4497**
14-15	(0.392951-0.439372)	158.087
15-16	(0.439372-0.44903)	118.78
16-17	(0.44903-0.49663)	133.166
17-18	(0.49663-0.514729)	147.763
18-19	(0.514729-0.525278)	126.322
19-20	(0.525278-0.557437)	145.613

Table 2: Phyllotaxic angles after label correction.

Leaves label	Height insertion (m)	Phyllotaxic angle (°)
from 1 to 11	... idem ...	... idem ...
11-13	(0.288003-0.35354)	**138.955**
13-12	(0.35354-0.346902)	133.72
12-14	(0.346902-0.392951)	**130.83**
from 14 to 20	... idem ...	... idem ...

4.5 Leaf Reconstruction

Finally for every segmented and labeled leaf, we have to compute its area. To achieve this, we need a surfacic representation. As presented in (Santos et al., 2015), we can use the NURBS fitting (Non Uniform Rational B-Splines) (Piegl and Tiller, 1997). The implementation and the procedure of NURBS fitting is described in (Morwald, 2012) and is available in PCL. These NURBS are then triangulated and the surface of a leaf can be obtained by summing the areas of each triangle that composes the NURBS. The area of a triangle is obtained with the Heron's formula, which consists in computing a triangle area by knowing the coordinates of its 3 vertices. Moreover, these NURBS can be more or less refined: an example of NURBS fitting applied on a single leaf with different levels of refinement is given in figure 10.

Figure 8: Result of leaf clustering.

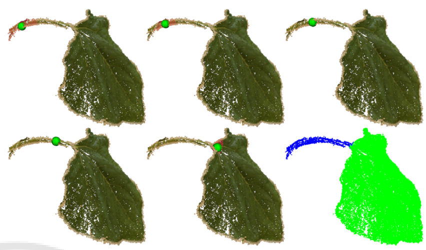

Figure 9: Example of ring reaching a leaf.

(a) 3D point cloud (b) Low refinement (c) High refinement

Figure 10: Comparison of NURBS fitting on a point cloud.

In the next section, the results of the segmentation will be commented, and the leaf area will be evaluated through a comparison with a manually obtained ground truth.

5 RESULTS AND VALIDATION

We have performed tests on a set of 10 plants from 6 different varieties to evaluate our method accuracy, repeatability and sensitivity to different sunflower variety. We performed an acquisition on each plant before cutting all leaves to estimate their area using a planimeter (a classical destructive phenotyping tool), to use this data as ground truth.

5.1 Acquisition

Evaluation experiments were made on isolated plant with images acquired under controlled illumination conditions. It showed that the acquisition method is well adapted for 3D sunflower reconstruction and can be used for 3D plant phenotyping. This method is time-consuming due to the number of required pictures and to the effort required to isolate the plant. This time can be reduced by using a mobile turntable, which could provide a medium-throughput phenotyping protocol.

5.2 Model-based Segmentation

The removal of the main stem in the 3D point cloud allows us to use the Euclidean Cluster Extraction to segment each leaf individually except for a few of them located under the top. This is due to:

- the resolution of the point cloud
- the proximity/contact between leaves on the top

The tests show that 83% of leaves available in the point cloud and longer than 6cm have been well segmented, as well as the use of the botanical sunflower model leads to a correct leaves labeling.

5.3 Leaf Reconstruction

After performing the tests, we can say that the NURBS fitting is well adapted for the reconstruction of flat leaves like the sunflower's leaves. Moreover, we compared the leaf area with the ground truth according to the refinement: results are given in table 3. This comparison shows that (1) the computed area is larger than the measured one, and (2) it is not useful to refine interpolation of the NURBS. The main reason is that the ground truth is obtained from a planimeter flattened the leaves and the more we refine the NURBS the more the NURBS fit the real leaf shape. If we do not increase the refinement, we obtain a flat shape of a leaf which is closer (in term of computed area) to a leaf passed through a planimeter.

Table 3: Comparison of the leaf area against the ground truth, with various NURBS refinement.

Number of refinement iteration	Leaf area
1	+10%
2	+14.5%
3	+18.4%
4	+22.2%

6 CONCLUSION AND FURTHER WORKS

This study presents a model-based segmentation of a 3D point cloud for sunflower phenotyping, with first applications for automated leaf labeling and individual leaf area estimation. First, a 3D point cloud of an isolated sunflower plant is obtained from an available Structure from Motion method, which could be adapted in order to make the procedure fully automatic. Then the main stem is extracted as well as the petioles insertions, using an original approach proposed to extract generalized cylinders. After that, Euclidean Cluster Extraction is applied, first on the petioles for labeling them and then on the rest of the point cloud to segment the leaves. This segmentation gives good results as well as the leaf reconstruction by NURBS fitting, but it shows also some limitations due to the acquisition process. However, the reconstruction is accurate enough to allow ecophysiological studies based on this method.

Aiming at fully automatize the acquisition procedure and to better segment the leaves, further investigations will be made in order to build a turntable that could be installed on a mobile robot. An alternative to Structure from Motion could be the Microsoft Kinect V2 which produces directly a 3D point cloud. As it was presented in (Chéné et al., 2012; Xia et al., 2015), the use of the Microsoft Kinect V1 allows to proceed plant phenotyping. The problem is that only one Kinect was used to perform top views' acquisitions; it does not allow the system to obtain a full model of a plant. Using at least 3 or 4 Kinect acquiring images simultaneously from different view points might allow to obtain a full 3D model of a sunflower, eventually by relying on the Microsoft Kinect Fusion software (Izadi et al., 2011). The resolution and the density of the outcome point cloud should be better than the one obtained by SfM with Bunlder+CMVS/PMVS but mostly the acquisition should be faster.

In addition, a temporal analysis will be performed in order to monitor the plant growth of the leaf area of a sunflower; it will determine if the labeling method could allow us to associate leaves extracted from the same plant at different periods and to perform a growth tracking on the leaves.

ACKNOWLEDGEMENTS

The authors would like to thank Céline Colombet, Philippe Debaeke, Nicolas Langlade and Pierre Casadebaig from INRA, Toulouse, for their participation to this work, through a joint project about high throughput phenotyping of sunflowers and the French National Research Agency (ANR) through the project SUNRISE.

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