Automated Surface Area Estimation of Plants based on 3D Point Clouds

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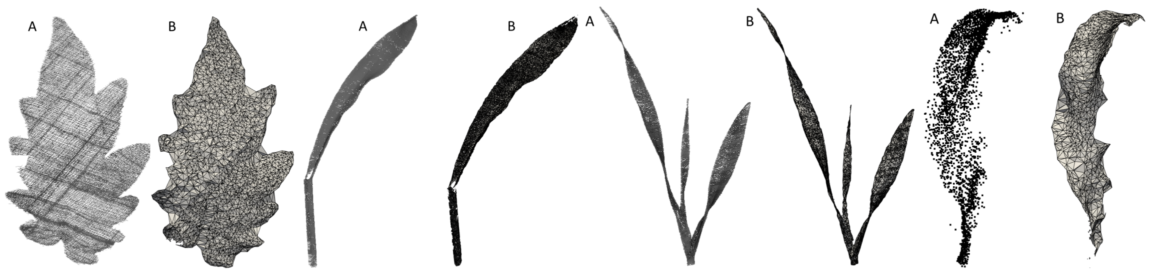
Plant phenotyping is a central task in crop science and plant breeding. Since standard methods often require time-consuming and manual observations it is indispensable to develop automatic, sensor driven methods which offer objective and fast information. Many methods rely on camera systems [2], ranging from RGB to hyper-spectral cameras. In recent years 3D sensing systems like laser scanners became increasingly popular [3, 7], since they provide structural plant parameters, which can be hardly extracted with spectral sensors. We present a pipeline for the extraction of plant surface areas, which reconstructs meshes from raw point clouds. This pipeline is completely automated with a robust set of empirically determined parameters, which we tested on different data sets. The few data set-specific parameters are determined directly from the respective data set and therefore do not need to be adjusted manually.

We investigate 4 different data sets, collected either in the laboratory with a handheld scanner (ScanWorks V5, Perceptpron, Hexagon Metrology Inc), or in the field with a mobile mapping system. Data set 1 and 2 consist of point clouds from 7 tomato and 7 maize plants respectively. The plants were observed over several days and manual leaf annotations are available [6]. Data set 3 contains scans of 4 barley plants, two under drought stress and two control plants. The plants were observed after the 24th day of sowing and were monitored 10 times over 21 days [5]. The field data set 4 contains a point cloud of a single maize plant (8 weeks after sowing, BBCH scale 32), which was recorded in an agricultural field using a mobile mapping system [4].

The input to the pipeline is a point cloud without any additional information such as RGB or intensity values. To transform point clouds into meshed surface several steps are required. Outliers are identified with an statistical approach which removes points further away from their neighbors compared to the average point distance of the whole point cloud. Based on empirical experiments we choose 5 neighbours and a standard deviation ratio of 1.0 as appropriate parameters. We uniformly sub-sample the point cloud which reduces the point number P to P/k. The down-sampling parameter k is determined directly from the data set itself by choosing a point density of 40 points per $1\,\mathrm{cm}^2$. We reconstruct the leaf surface using the Ball-Pivoting algorithm [1] which creates a triangle mesh of a point cloud. The Ball-Pivoting-radius ρ depends on the average distance between the points. A ball with the radius ρ is placed three times on the surface, each time with a scaling factor. In order to generate a mesh with as few gaps as possible, a scaling with 10 has proven to be appropriate for plants. We find the remaining holes in the surface reconstruction, extract them and fill them with a flat surface. As a last step the surface area can be determined by adding up the areas of the individual triangles.

The pipeline is implemented using Open3D [8]. We use the same set of parameters for all experiments to highlight the robustness of our approach. Figure 1 shows examples of the four different datasets. We process the leaves of the 7 tomato plants of datset 1 automatically and determine the surface area of each individual leaf. Figure 1(a)**A** shows an example of a single leaf point cloud of data set 1. It can be seen that the handheld scanner acquires high density point clouds. The result of our pipeline can be seen in figure 1(a)**B**, which shows the triangulated mesh. In figure 2(a) an example of the surface growth of each leaf of one tomato plant can be seen. We observe increasing growth over the entire measurement period, although the first two emerging leaves (*cotyledons*) of the tomato show a lower growth rate compared to the other leaves, probably due to the fact that these leaves capture less light than the leaves in the upper part of the plants. The total surface area of the tomato leaves range from $2\,\mathrm{cm}^2$ to $311\,\mathrm{cm}^2$.

An example for a single maize leaf point cloud of data set 2 is shown in figure 1(b)**A** and the reconstructed leaf surface in figure 1(b)**B**. It can be seen that the maize leaves have more holes due to the measuring process and tend to twist and bend. This makes reconstruction more difficult, but our pipeline is able to reconstruct these leaves success-



(a) Tomato (b) Maize (c) Barley (d) Field Maize

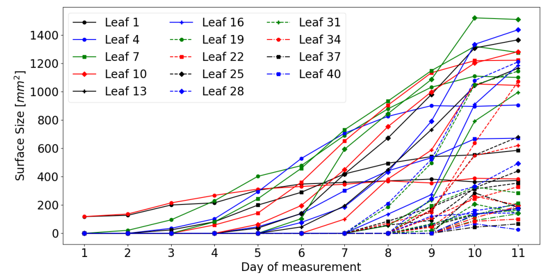
Figure 1. For all sub-figures holds: **A** shows the point cloud and **B** shows the reconstructed surface by using our pipeline.

fully. Compared to the tomato plants of data set 1, the total surface area of the maize plants is smaller, it starts at $1\,\mathrm{cm}^2$ and goes up to a maximum of $74\,\mathrm{cm}^2$.

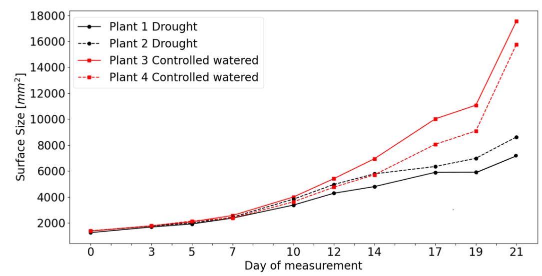
The barley plants were measured over a period of several days, which enables a plant growth analysis. In addition, 2 plants were exposed to drought stress while the other 2 plants worked as control plants. Figure 1(c)**A** shows the point cloud of one exemplary barley plant. We observe a similar behaviour as the tendency to twist and bend compared to the maize plants from data set 2. The reconstructed surface by using our pipeline is shown in figure 1(c)**B**. The surface growth of the 4 barley plants can be seen in figure 2(b). As expected, we observe a large difference in the surface area between the control and the drought stress plants. From the 10th day of the measurement we observe a lower growth rate of the drought stress plants. While the control plants reach a surface size between $161\,\mathrm{cm}^2$ and $177\,\mathrm{cm}^2$, the drought stress plants only grow up to $72\,\mathrm{cm}^2$ and $91\,\mathrm{cm}^2$.

Furthermore we test our pipeline on one exemplary field data set to investigate the robustness of our pipeline under field conditions. The point cloud of one exemplary leaf is shown in figure 1(d)**A**, while the reconstructed surface of this leaf is shown in figure 1(d)**B**. The surface area of the whole maize plant was calculated as $991\,\mathrm{cm}^2$. As expected, this is significantly larger than the area of the maize plants in data set 2, since the maize plant in the field was measured in later stage in the growth period.

Although we successfully applied the pipeline to different data sets, there are still some requirements on the quality of the input point cloud. Firstly, the point density and the noise of the sensor have to be sufficient enough, that single leaves can be recognized in the point cloud. Both sensors used in this paper had this properties, but other mostly low cost devices, such as stereo cameras or automotive grade laser scanners may not be good enough, especially for small leaves. Another important quality parameter is the completeness of the data. Of course we can only measure what we can see, so the measurement procedure mainly determines this. Data sets 1 to 3 have a high completeness due to the manual movement of the scanning device. Data set 4 is scanned from above, so some occlusion of lower leaves are very likely. In the future, we will concentrate on automatically recorded time series within agricultural fields to evaluate the above criteria in non-laboratory conditions.



(a) Tomato



(b) Barley

Figure 2. Top: Exemplary surface growth of all leaves of one tomato plant. Each line describes one leaf of the entire plant. To increase readability, only every third leaf of the in total 42 leaves of the tomato plant are labelled in the legend of the figure. Bottom: Surface growth of 4 Barley plants. Two plants are well watered over the whole measurement period (controlled watered) and two are under drought stress (drought).

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