Measuring Ground Truth for 3D Reconstruction of Plants

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Figure 1: Images of plants (top) and corresponding point clouds (bottom). Left to right: Plant 1 (*Aechmea fasciata*), Plant 2 (*Haworthia attenuata*), Plant 3 (*Euphorbia milii*), Plant 4 (*Crassula ovata*) and Plant 5 (*Peperomia caperata*). The right side shows the setup used to scan the plants

3D object reconstruction from camera images is a standard problem of computer vision with a multitude of solutions [2, 8, 11]. However, accurate and reliable automated measurements of 3D plant shape are not yet available for complex plants despite image-based analysis of plants being well established (see *e.g.* [1, 5, 10, 13] and many more). Ground truth data with accuracy bounds for multiview 3D object reconstruction is publicly available [3, 12]. However for plant reconstruction no such data can be found in the public domain. Therefore, the primary objective of this research is to develop a method for generating 3D points clouds of plants, such that they can be used as *ground truth* for other experiments. Clearly, better ground truth data will enable better analysis [4].

Here, we use a stereo-camera-based *structured light scanner* (*LMI HDI Advance R4x* [6] see Figure 1) for capturing depth information from five different specimens (Figure 1). This scanner has been tested to be well suitable for high accuracy point cloud reconstructions [9]. We selected this scanner, as systems based on laser line projection which potentially yield even higher accuracy [9] are less reliable on highly complex surfaces with rich occlusion like plants.

For plants of the overall size considered in this study (max. of $\approx$ 40cm diameter or height) the widest camera configuration and 16mm lenses were selected due to field of view constraints. The system provides a rotary table to automate the scanning process. The software *FlexScan3D* [7] is used for merging, aligning and finalizing the scans. Alignment errors between individual scans are typically well below 10μm.

Additionally, geometric accuracy of the instrument was obtained using calibration objects and error sources were investigated with the help of self-designed contrast boards.

This study shows that it is possible to obtain point clouds of geometric calibration objects (shere, cube, cylinder) with an overall accuracy of 0.087mm. On plants we observed that with the presented method, the upper and underside of leaves could be reconstructed individually, where the thinnest leaves were 0.6mm thick. Petals (Plant 3) in the range of 0.4-0.6mm thickness could also be reconstructed, but the point clouds turned out to be too cluttered to distinguish upper and underside. Elongated plant parts, *e.g.* thorns and stems (Plant 3, 5) thinner than 0.2mm could be imaged, but were not reconstructed by the applied method.

We observed that reconstruction accuracy is affected by problematic surface properties like glossy leaves producing specular reflections (Plant 4) or plant movements induced *e.g.* by the rotary table. Plant movements can be reduced by reducing rotary acceleration. Reflections may be reduced by anti-glare spray, but we did not further investigate this effect. Also Lambertian surfaces of different gray values (intensities) are reconstructed at different depths. This inaccuracy shows no clear systematic dependency on other measurements, like the gray value itself or local contrast. We therefore treat it as stochastic error introducing a maximum deviation of up to 0.25mm. This is well consistent with the findings in [9].

Overall the observed errors sum to $<\approx$1mm as worst case estimate. Expected errors are well below this value. The overall performance of the method can be evaluated by projecting the derived 3D point cloud models back into acquired images and inspecting differences of the outlines of the plants and models. We observed no or only subpixel mismatches for most surfaces. However for the outermost plant parts with the largest distances to the plant center we observed up to $\approx$ 5 pixel offsets (esp. at the very leaf tips), corresponding to ≈ 1.25mm error.

The acquired data sets together with the detailed accuracy analysis may be used to define a benchmark analogous to previously published ones [3, 12].

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