Building 3D Models of Field-Grown Maize

Dewi Endah Kharismawati* and **Toni Kazic**

Dept. of Electrical Engineering and Computer Science, University of Missouri, Columbia, USA
Missouri Maize Center
Interdisciplinary Plant Group

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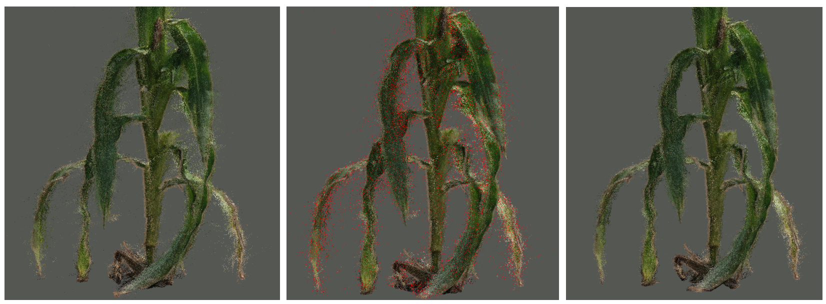
Abstract: Many morphological phenotypes are three dimensional and are not fully captured by planar projections. 3D reconstruction would be ideal for capturing these phenotypes, but reconstruction of plants is more challenging than hard surfaced, geometrically more regular objects due to their thinness, soft edges, and irregular shapes. Directly reconstructing field plants is even harder since they move easily with air currents, with different parts of the plants moving with different periods and amplitudes. Algorithmic 3D reconstruction is computationally expensive, leading to the adoption of more efficient and adaptive deep learning techniques. However, the point clouds used for training must be of high quality. The available datasets in this domain commonly consist of potted plants captured indoors (Artzet et al., 2019; Choudhury et al., 2020; Wang et al., 2019). These data do not reflect the challenges of real field conditions and networks trained on these data might not be transferable to field scenarios.

Our goal is to reconstruct maize plant and organ morphology. In the 2021, 2022, and current 2023 field seasons, we planted selected maize lines in a triangular tiling, spacing them at radii of 3m (2021 season) or 4.6m (2022, 2023 seasons). Unmanned Aerial Vehicles (UAV) were flown at 1–2m distance with two different orbiting trajectories and camera poses to capture video. The first orbit was captured with a camera pose parallel to the plane of the soil, at approximately 1m above the soil (about half the plants' heights). The second orbit was captured at 2–3m with an oblique view (slightly higher than the plants). A portion of the tiling field is shown in Figure 1a. We used COLMAP to compute a dense 3D reconstruction of the entire tiling and individual plants (Figures 1b and 1d) (Schönberger and Frahm, 2016). We manually removed extraneous points from reconstructions of individual plants using MeshLab (Cignoni et al., 2008).

The 3D reconstructions are suprisingly good. Figures 1b and 1d show the unimproved COLMAP reconstructions of a portion of the tiling field and an individual plant. Two types of artifacts occur. The first type is voids in the reconstruction from gaps in the point cloud, highlighted in Figure 1c as yellow pixels. We are now testing how well these gaps can be eliminated by adding trajectories that image the same region of the field within a narrow temporal interval and at multiple camera poses. The second is outliers of motion or color. Motion outliers of the plant's organs are induced by air currents and are visible as points scattered away from the main mass of the point clouds (Figure 1d) and as ghost organs (data not shown). We computed a rough assessment of outliers using the z_{score} defined as $z_{\text{score}} = \frac{x-\mu}{\sigma}$, where x is the pairwise distance between a point and its nearest neighbors, μ is the mean of the distances, and σ is their standard deviation. The red motion outliers for an individual plant are shown in Figure 1e. Color outliers reflect the color of the surrounding objects. Two examples are soil-colored outliers in the bottom half of the point cloud (Figure 1d, in the space at the bottom of the plant) and sky-colored outliers surounding the tassels (Figures 1b and 1c).

Removing these outliers is vital for better training data. Figure 1f shows the result of manually removing most of just the motion outliers from the raw point cloud of Figure 1d, a slow process. We are now comparing several outlier removal methods, including a distance statistical method using the z_{score} and several deep learning approaches, such as PointCleanNet (Rakotosaona et al., 2019).

(a) Raw RGB frame. (b) 3D tiling. (c) Voids (yellow).



(d) 3D plant. (e) Outliers (red). (f) Manual cleaning.

Figure 1: 3D reconstructions and artifacts: a portion of the tiling field (top) and a plant of interest (bottom).

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