Book of Abstracts

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Realtime input of sensor-based phenotypic traits for functional-structural plant modelling of tomato

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Introduction

Functional-structural plant (FSP) modeling has been widely applied to study plant performance by simulating 3D plant architecture and functioning in response to environmental drivers (Evers and Marcelis, 2019). To develop an accurate plant model and track the interaction between the plant growth and the environment, quantification of phenotypic traits of plants at different growing stages is required (Cieslak et al., 2022), we call it a "phenotype-to-model" approach. Currently, phenotypic traits of plants are generally measured manually, which is exceptionally time consuming. 3D high-throughput automatic phenotyping techniques provide feasible solutions towards this problem through sensor-based data acquisition and processing. However, the complexity of tomato plant architecture and serious occlusion among organs make this phenotype-to-model approach challenging. To further investigate the performance of this phenotype-to-model pipeline applied to tomato plants, four types of phenotypic traits (stem internode length, stem internode diameter, leaf branching angle and leaf phyllotactic angle) were quantified using point cloud processing techniques. These estimated traits can be used to update related parameters and states of an FSP model developed for tomato plants.

Materials and Methods

The overall mechanism is revealed in Figure 1. An FSP model was developed to simulate growth of a tomato plant. An automatic phenotyping pipeline was developed to acquire the phenotypic traits by taking point clouds of tomato plants as the input. An imaging system in the Netherlands Plant Eco-phenotyping Centre (www.npec.nl) was used to acquire tomato plant point clouds. The imaging system contains 15 cameras mounted in a cylindrical-shape black box from different perspectives. Fifteen synchronised images of the object were captured with these cameras at each imaging moment, and a coloured point cloud was then reconstructed with the shape-from-silhouette method (Golbach et al., 2016).

The phenotyping pipeline contained two parts: 1) a deep-learning-based point cloud segmentation to identify and localise the plant skeleton; 2) a tree quantitative structural modeling (TreeQSM) algorithm (Raumonen et al., 2013) to achieve the morphological analysis of the skeleton point cloud and the calculations of relevant parameters. To segment the point cloud into plant parts, we employed one of the top-performing deep neuron networks – PointNet++ – as the backbone (Qi et al., 2017). Together with data augmentation techniques, a clean plant skeleton point cloud was obtained, and was then taken as the input of TreeQSM algorithm. TreeQSM performed a morphological analysis of the input point cloud to divide individual points into morphological orders, i.e. stem, secondary branches (petioles) and tertiary branches (petiolules). Cylinder fitting was applied to the point cloud using least square algorithm, where parameters of each meta cylinder, including cylinder length, cylinder diameter and cylinder orientation vector, were calculated. Relevant plant traits were finally obtained by combining relevant cylinder candidates within the same internode.

Four tomato plants from two commonly used tomato plant cultivars (Merlice and Brioso) were used to test the preliminary performance of the proposed phenotyping pipeline, where three of them were Merlice and one was Brioso. Destructive measurements were conducted on those plants in order to obtain the ground truth values.

Preliminary Results and Discussion

The average absolute error of stem internode lengths, stem internode diameters, leaf branching angles and leaf phyllotactic angles were $22.5\,mm$, $3.1\,mm$, $15.3\,°$ and $23.2\,°$ respectively. A potential reason for the bias was the limitations on point cloud density. Within a point cloud, the separability of parts close to the morphological top of a plant was poor, which resulted in a relatively poor segmentation of the plant skeleton. This can be further dressed by employing a higher resolution during the point cloud reconstruction from the images. In the next steps, the performance of the FSP model with the interaction with the real sensor data will be measured by comparing predicted shoot dry mass with the actual destructive measurements.

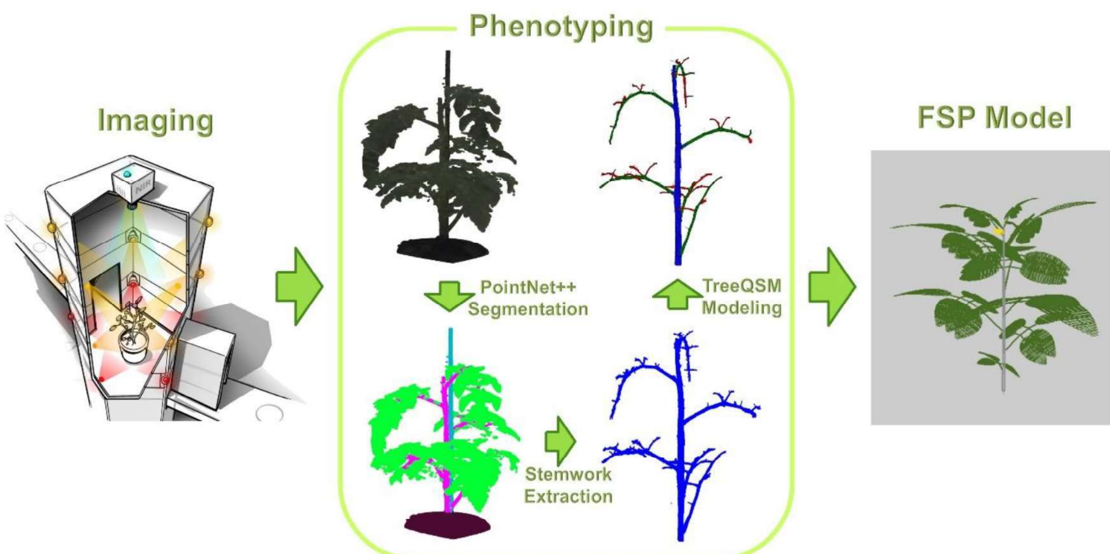

Figure 1: Pipeline of the proposed phenotype-to-model approach for tomato plants.

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