# Automated vegetable growth analysis from outdoor images acquired with a cablebot.

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Computer vision methods in plant phenotyping made great improvements with the introduction of deep learning algorithms and plant monitoring devices. This offers the possibility to study the growth of plants at large scale. It should be noted that a large portion of the research is dedicated to indoor plant cultivation. This is in part due to the challenge of obtaining data in outdoor environment regularly and to the challenge of processing the acquired data. We present an automated way to acquire in-field data as well as the image processing pipeline to extract plant growth data.

Other research works has adressed this challenge using 3d reconstruction techniques [1, 3] but we noticed the resulting point clouds are noisy so we considered instead the evaluation of plant growth based on the projected leaf area as estimated from 2d images. One of the main difficulties we had was in the registration of image to a common frame because images of crops change aspect along time.

The image acquisition device is a cablebot: a camera attached to a motorized actuator moving on a linear axis. The cable can be attached to a greenhouse or to poles planted at the border of the crop bed to be monitored. An single board computer (Raspberry Pi) is embedded on the cablebot to command the motor and to upload regularly the acquired images to a server.

For each acquisition, a global picture of the crop bed is composed by stitching together the acquired images. The cultivars (in our case lettuces) are then segmented on this image and we tested 4 methods to achieve this goal. A first method is thresholding based on the green excess index, a second and third method is to train an SVM or CNN performing semantic segmentation of the image into ground and lettuces and finally, fourth method is based on a deep learning architecture [2], Mask-RCNN, and detects lettuces by providing a mask for each plant. We also tested two methods to track individual plants. In a first method, we register all maps to a common frame using feature matching and detected plant at initial growth stage. The area around each plant is then considered in all images for measuring each plant size as approximated by the projected leaf area. In a second method, we detect each plant in each image and align the resulting point clouds in consecutive images. Again, the projected leaf area is measured based on the segmented masks. The data is then collected over time to get a growth curve for each plant. The curves are then aggregated to reach statistics about the growth of plants and modeled using a logistic growth curve.

We show that, through processing using computer vision algorithms, the cable bot is an efficient way to collect data that are relevant for in-field plant phenotyping. To complement the analysis, we also present an integrated dashboard summarizing all data and processing.

## References

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