Watershed and supervised classification based fully automated method for separate leaf segmentation

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Introduction

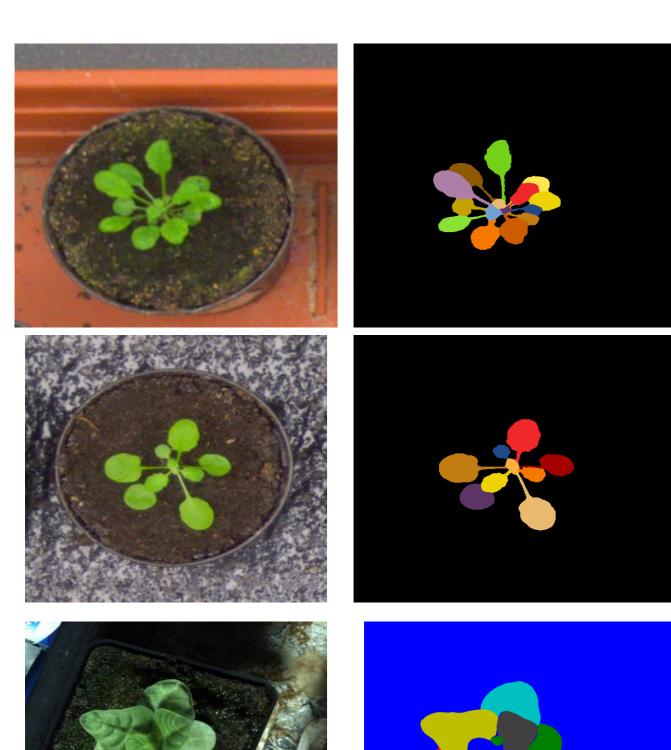


Figure 1. RGB top-view images (left) and the ground truth images with manually labelled leaves (right).

In order to perform large-scale plant breeding, it is important to be able to automatically measure relevant plant characteristics: plant size and the individual leaves growth. We present a method for fully automated plant leaf segmentation for top view images of rosette plants of the following species: Arabidopsis thaliana and tobacco (Fig. 1). The images are made in different light conditions, different stages of development, various presence of moss in the soil and with highly overlapping leaves.

Methods

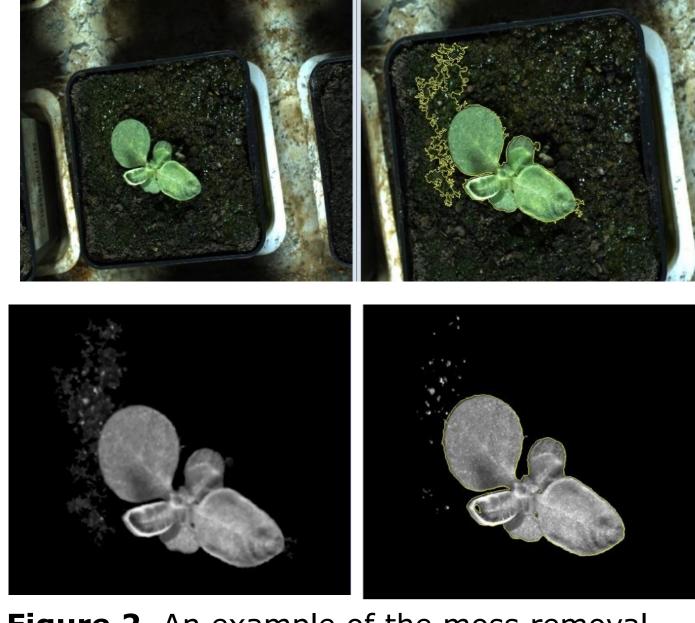


Figure 2. An example of the moss removal method applied on the neural network based segmentation (top right). After the thresholding of the X-component of the RGB-XYZ colour transformation (bottom left), the final plant segmentation is calculated (bottom right).

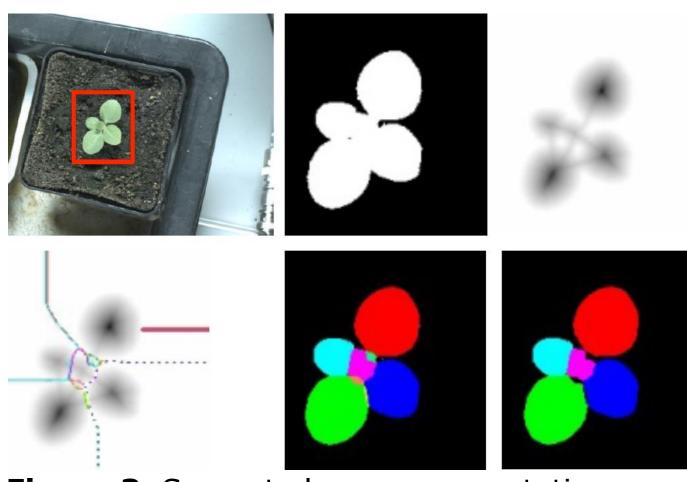


Figure 3. Separate leaves segmentation method steps: plant segmentation (top centre), Euclidean distance map (top right), watershed method applied on the distance map (bottom left), intersection of the watershed image and the plant segmentation (bottom centre) and the separate leaves segmentation after discarding small components (bottom right).

The method consists of two steps: plant segmentation and separate leaves segmentation.

- Plants segmentation against the background, was done using supervised pixel based neural network classifier. For each pixel 6 features are used: R, G, B and excessive Green (2G-R-B), the pixel values of the variance filtered green channel, and the pixel values of the gradient magnitude filtered green channel. Propagation, blobs and moss removal were done on the classification result images (Fig. 2).
- The second step, separate leaves segmentation (Fig. 3), was achieved using a watershed method utilized on the Euclidean distance map of the resulting plant mask image of the first step of the method. Initially, the watershed transformation is computed without applying the threshold between the basins. In the second step, the basins are successively merged if they are separated by a watershed that is smaller than a given threshold. The threshold value was tuned in order to produce the best result.

Results

The method was tested on the highly challenging data set provided by the Leaf Segmentation Challenge 2014 (http://www.plantphenotyping.org/CVPPP2014-challenge). The Dice indices for the plant and separate leaves segmentations on the train and test set are presented in the tables bellow.

To the best of our knowledge, the results of our segmentation method on the train sets A1 and A2 and on all the test sets are the best of all the published results of the algorithms tested on this dataset.

Train Set (236)	Plant Segmentation	Leaves Segmentation
A1	96%	74%
A2	95%	75%
A3	96%	70%

	Test Set (70)	Plant Segmentation	Leaves Segmentation
	A1	95%	71%
	A2	95%	76%
_	A3	90%	58%



Figure 4. Automated separate leaves segmentation results: test images (left), separate leaves labelled by an expert (centre) and automated leaves segmentation (right).

Conclusions

We have developed a fast (\sim 150ms per image), fully automated seperate leaves segmentation algorithm that is tested on a publicly available, annotated, large RGB top-view dataset. The method achieved better results than any other method evaluated on this dataset. The results are highly promissing given the complexity of the problem and it brings us one significant step closer towards fully automated, large-scale plant phenotyping.