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

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Abstract

In this paper we present a method for fully automated plant leaf segmentation for top view images of rosette plants of the Arabidopsis thaliana and tobacco species. The images are imaged in different light conditions, different stages of development, various presence of moss in the soil and with highly overlapping leaves. All these characteristics make the test dataset highly challenging. The method consists of two steps: pixel classification based plant segmentation and watershed based separate leaves segmentation. The Dice index for the complete plant segmentation was 0.95, 0.95 and 0.90 for the three testing subsets. The separate leaves segmentation Dice index was 0.71, 0.76 and 0.58 for the three testing subsets. The method achieved the highest accuracy on the given dataset compared to all the methods published to date.

1. Introduction

The study of a plant's phenotype, i.e., its performance and appearance, in relation to different environmental conditions is central to understanding plant function. Identifying and evaluating phenotypes of different cultivars (or mutants) of the same plant species, is relevant to, e.g., seed production and plant breeders. One of the most sought-after traits is plant growth, i.e. a change in mass, which directly relates to yield. To investigate general plant performance biologists grow model plants, such as Arabidopsis (*Arabidopsis thaliana*) and tobacco (*Nico-tiana tabacum*), in controlled environments and monitor and record their phenotype. While previously such phenotypes were annotated manually by experts, recently image-based nondestructive approaches are gaining attention among plant researchers to measure and study visual phenotypes of plants.

For rosette plants nondestructive measurement via images of a plant's projected leaf area (PLA), i.e. the counting of plant pixels from top-view images is considered a good approximation of plant size and is currently used. However, when considering growth, PLA reacts relatively weakly, as it includes growing and non-growing leaves, but the per leaf derived growth (implying a per leaf segmentation), has a faster and clearer response. Thus, for example, growth regulation and stress situations can be evaluated in more detail. Additionally, since growth stages of a plant are usually based on leaf number an estimate of leaf count as provided by leaf segmentation is beneficial.

However, obtaining such refined information at the individual leaf level, which could help us identify even more important plant traits, from a computer vision perspective is particularly challenging. Plants are not static, but self-changing organisms with complexity in shape and appearance increasing over time. In the range of hours leaves move and grow, with the whole plant changing over days or even months, in which the surrounding environmental (as well as measurement) conditions may also vary.

The method presented in this paper was trained and tested on the highly challenging data from the Leaf Segmentation Challenge (LSC) of the Computer Vision Problems in Plant Phenotyping (CVPPP 2014) workshop [1], held in conjunction with the 13^{th} European Conference on Computer Vision (ECCV) (Figure 1). This method is presented at the COST conference [1] and in the collation study [2].

2. Methodology

The method consists of two steps: plant segmentation and separate leaf segmentation, illustrated in Figure 2. Plant segmentation from background was done using supervised classification with a neural network. Since the nature of the three datasets ($A1$, $A2$, and $A3$) is different, a separate classifier and post-processing was performed for each individual set. The ground truth images were used to mask plant and background pixels. For all images 3000 pixels of each class are randomly selected for training. When the plant is smaller than 3000 pixels, all plant pixels were used. For

[1] http://www.plant-phenotyping.org/CVPPP2014

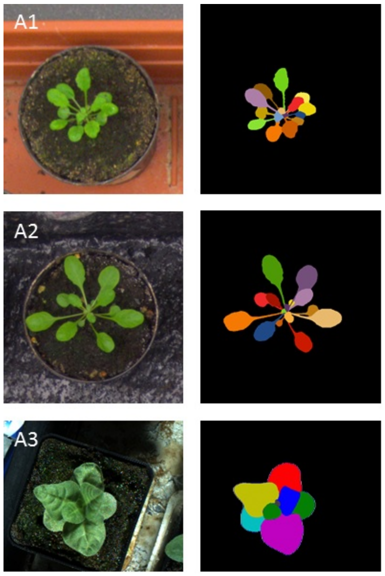

Figure 1. Example of images of Arabidopsis and tobacco from the datasets used.

each pixel 6 features are used in the classification: R, G, B, 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. A large range of linear and nonlinear classifiers were tested on each dataset, with a feedforward (MLP) neural network with one hidden layer of 10 units giving the best results. Morphological operators on the binary image obtained after plant classification and on the color transformations of the original RGB image result in the plant masks (FGBG).

The second step, separate leaves segmentation, was achieved using a watershed method [3] utilised 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 on the training set in order to produce the best result. The thresholds were set to 30, 58 and 70 for the datasets $A1$, $A2$, and $A3$ respectively.

3. Results

The Dice index for the foreground vs background segmentation of the complete plant was 0.96, 0.95 and 0.96 for the training datasets $A1$-$A3$ respectively. The separate leaves segmentation Dice index was 0.74, 0.72 and 0.70 for the datasets $A1$-$A3$ respectively. This result is the same for $A1$ and significantly better for $A3$ compared to the challenge winner result.

On the test set the accuracy of the method decreased.

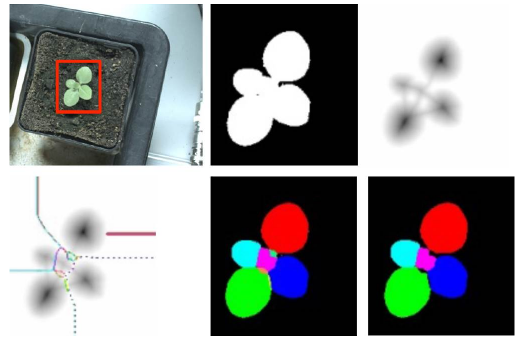

Figure 2. Separate leaves segmentation method steps: plant segmentation (top centre), Euclidean distance map (top right), watershed method applied on the distance map (bottom left), intersection of the watershed image and the plant segmentation (bottom centre) and the separate leaves segmentation after discarding small components (bottom right).

Figure 3. Automated separate leaves segmentation results: test images (left), separate leaves labeled by an expert (centre) and automated leaves segmentation (right).

The Dice index for the complete plant segmentation was 0.95, 0.95 and 0.90 for $A1$, $A2$ and $A3$ respectively. The separate leaves segmentation Dice index was 0.71, 0.76 and 0.58 for the $A1$, $A2$ and $A3$ set respectively. The separate leaves segmentation accuracy of our method is higher than of any other method reported on this dataset. An example of the automated leaf segmentation is presented in Figure 3.

References

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