A Hierarchical Framework for Leaf Instance Segmentation: Application to Plant Phenotyping

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Introduction

- Quantification of morphological plant traits is a key component of precision agriculture [1].
- Traditional plant phenotyping is based on destructive sampling of plants from the fields and manually measuring the phenotypes however, this is a labour intensive process.
- In contrast, image based phenotyping is a non-invasive process that allows temporal study of plant phenotypes. Thus, many image based phenotyping platforms have been established that enable growth modelling of thousands of plant canopy [2].
- For studying growth, per leaf derived phenotypic traits such as leaf area, leaf length, leaf area index etc. are accurate indicators
- **A prerequisite task for computing these leaf derived traits is segmenting each leaf from the plant image.**
- This is a **challenging task** due the presence of **various degrees of overlap** among plant leaves, **variability in leaf pose** and the **number of leaf instances is unknown a priori**. In addition, the **lack of discernible boundaries among these overlapping leaves** adds to the complexity of the task even in the controlled imaging of plants [3].

Introduction

- **Thus, the focus of this paper is multi-instance leaf segmentation with typical imaging conditions.**
- Within the **limited literature of leaf instance segmentation, two different categories of approaches** exists:
- (a) **Traditional computer vision-based methods.**
- (b) **Deep neural networks**.
- Deep learning architectures proposed in this context requires a significant amount of labelled data as well as a large network to examine all the combinations of leaf, size, shape, orientation, and curvatures [4-6].
- However, labelling leaf instances is manually extensive and due to large inter-class variability in leaf shapes, the trained model on one plant species dataset is not directly applicable to other plant species this is also due to the difference in growth pattern.
- This paper attempts to automate the step of obtaining leaf shape knowledge as shape priors and utilise these priors in a template-based approach for leaf instance segmentation.

Contributions

- The paper has the following **contributions:**
- **The novel strategy to exploit the global feature of leaf shape i.e. symmetry about the medial axis.**
- **The automatic generation of leaf templates for the incorporation of leaf shape knowledge in the leaf instance segmentation framework.**
- **This permits the analysis of different plant cultivars with rich leaf shape variation, thus relieving the current bottleneck of annotated data .**

Dataset

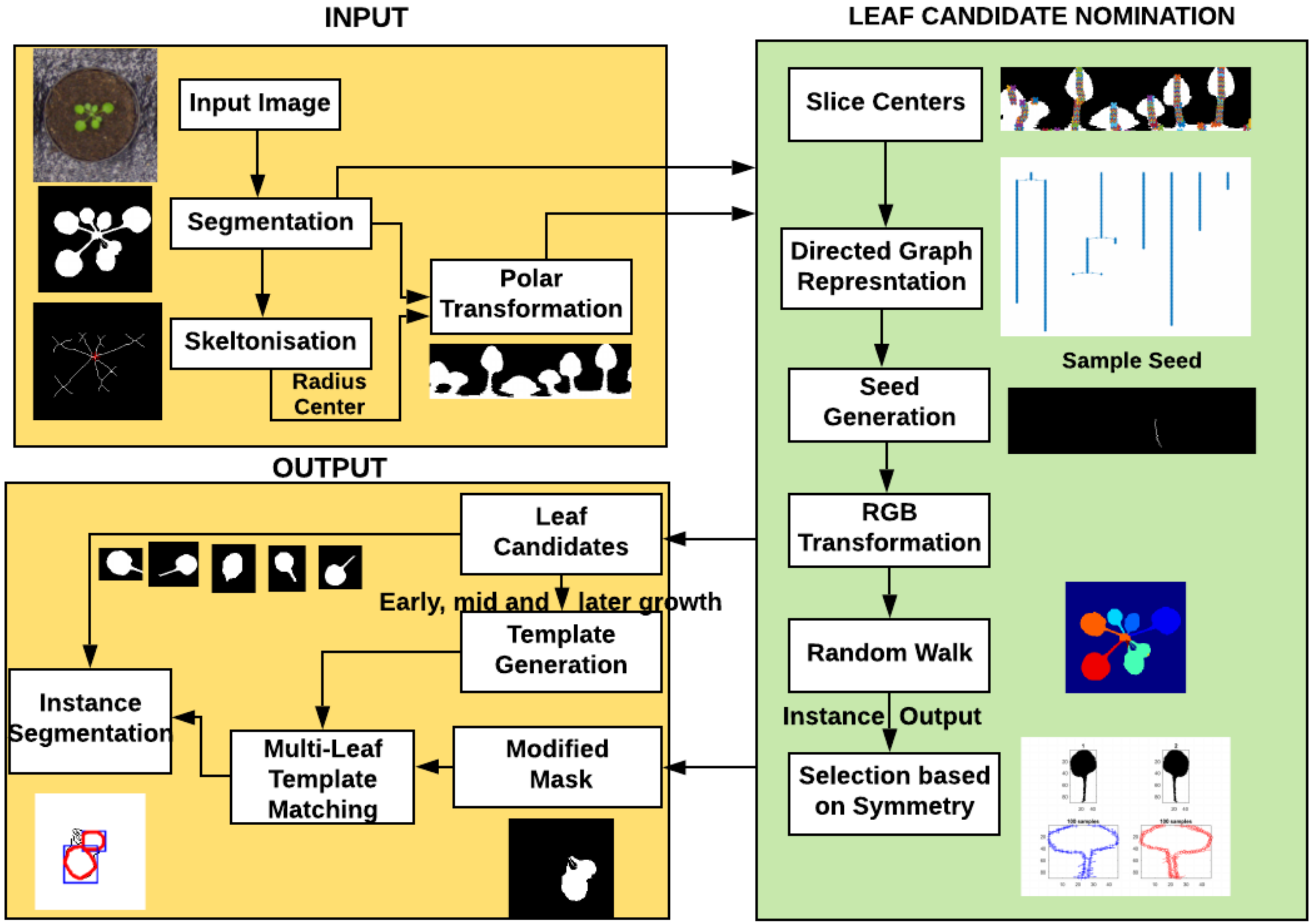
- The evaluation of the proposed framework is shown on the following datasets, consisting of top-down views of different plant species collected at different growth periods and the corresponding ground truth instance segmented images that has been manually annotated by experts:
- PRL dataset [7,8].
- The plant phenotyping database [9].
- The Komatsuna dataset [10];
- The Salad dataset [11].

Proposed Framework

- A hierarchical framework comprising of two-stage is proposed:
- **The first stage allows the isolation of leaf candidates based on their symmetric nature [12], this step is accomplished using random walk algorithm [13] with seeds automatically generated from the directed graph representation [14] of the plant image.**
- **The second stage utilises the multi-leaf alignment algorithm [15] that aligns multiple overlapping leaf instance in an image with given template database**.

- The leaf candidates generated in the first stage are used for automatically synthesising template database using affine parameters (rotation and scaled). These representative leaves with its structure information (i.e. leaf tips) are used in the aforementioned multi-leaf optimisation framework to extract individual leaves.

Proposed Framework

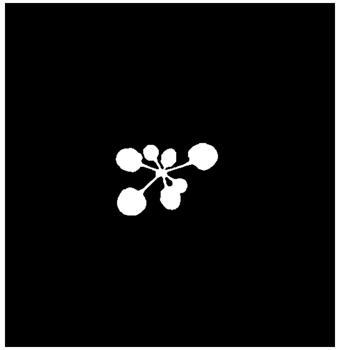


Proposed Framework

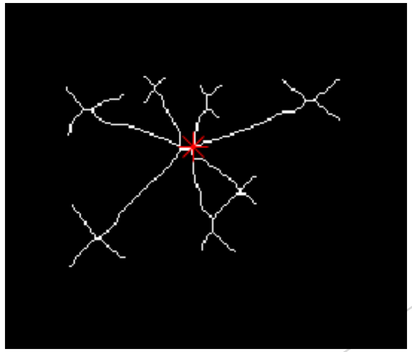
- The plant canopy consists of leaf instances with different orientations, we first transform the top-view images into polar coordinates (resulting in all the leaves pointing in the same direction).
- The centre and the radius required as an input for the polar transformation is extracted using the skeletonised graph of the top-view image and utilising its node properties i.e. betweenness and maximum path length.
- Betweenness [16] is a measure of the centrality of a node in a graph, and is normally calculated as the fraction of shortest paths between node pairs that pass through the node of interest.
- Since, the plant always grows from the centre and all the leaves connected to the centre, the node with the maximum betweenness is labelled as the centre and the maximum path length of all the end nodes from this centre is used as the radius (see figures below).

RGB TOP-VIEW IMAGE

SEGMENTED IMAGE



SKELTON (centre marked in red)

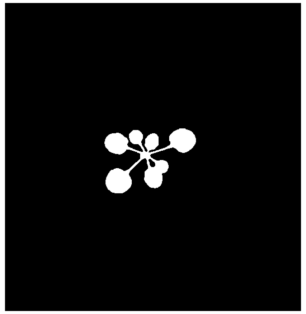


Proposed Framework

- The image is polar transformed using the following equation [14] :

$$P(r,\theta) = I\left(\left\lfloor C_x + r\cos\left(\frac{\pi}{180}\theta\right)\right\rceil, \left\lfloor C_y + r\sin\left(\frac{\pi}{180}\theta\right)\right\rceil\right)$$

SEGMENTED IMAGE



POLAR TRANSFORMED IMAGE

- Then we utilise the slice representation [14] (a set of connected pixels at a fixed radius r) to obtain hierarchical relationship (parent-child) between pixels. The slice with a smaller r is denoted as a parent of the child with a larger radius. Based on this relationship, a directed graph is constructed.

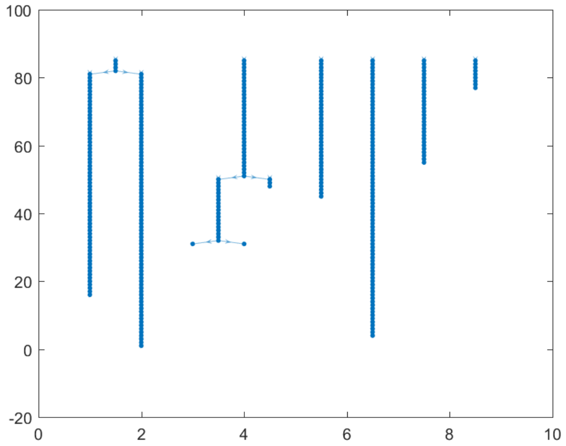
POLAR TRANSFORMED IMAGE

SLICE BASED MAPPING

Proposed Framework

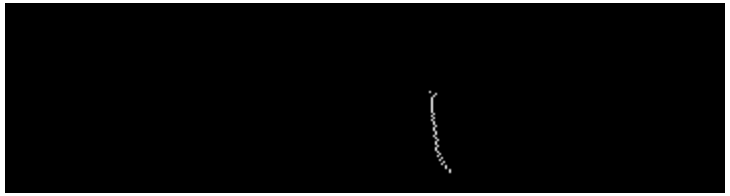
SLICE BASED MAPPING

SLICE BASED HIERARCHICHAL REPRESENTATION (Directed graph)

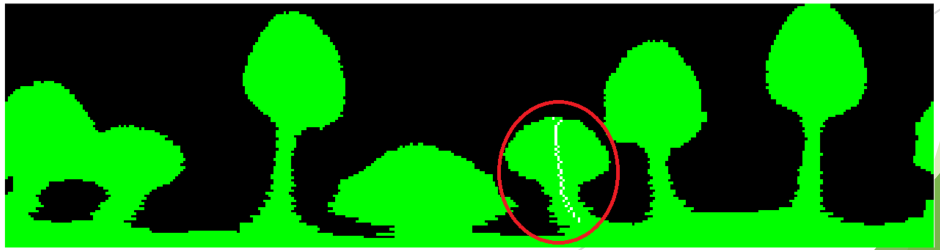


The path between the source and end nodes of the directed graph (as shown above) is obtained. Sample image of such path is shown below.

SAMPLE PATH

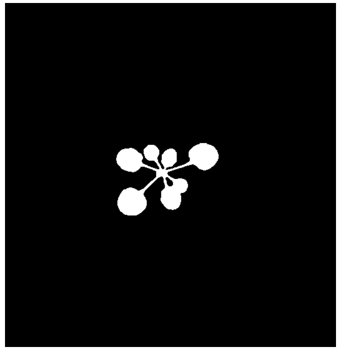


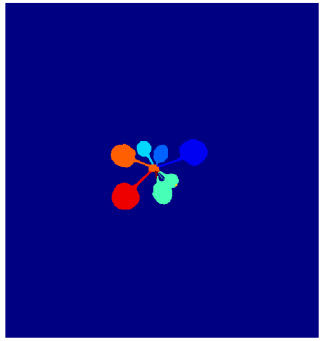
VISUALISATION



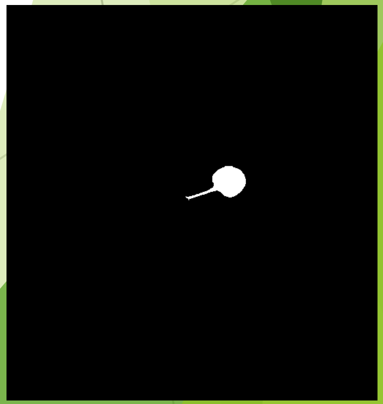
Proposed Framework

- These path are then transformed back from the (r, theta) plane to the (x, y) plane and utilised as input seeds for random walk segmentation [13].
- The output of the random walk segmentation on these extracted seeds are shown below (different colour corresponds to different instances):



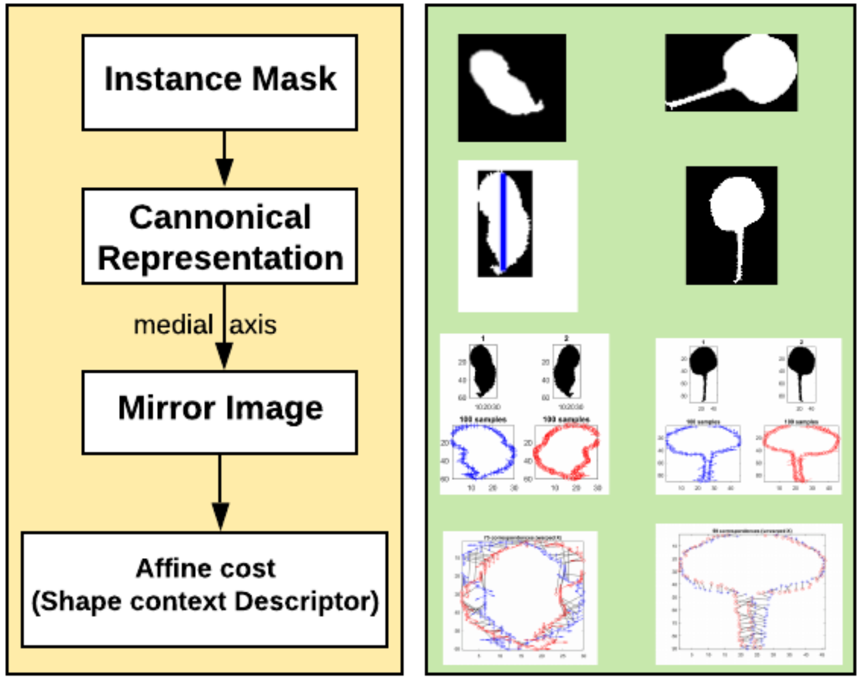


- The leaf instances from the labelled mask is extracted (a sample image shown on the right).
- It can be observed from the random walk output that the all the non-occluded leaves are extracted accurately.
- To separate the accurate leaf instances from the inaccurate instances, a symmetry test is used. The basis of this test is that the leaf shape is symmetric about the medial axis (i.e. a line joining the two end tips.)



Proposed Framework

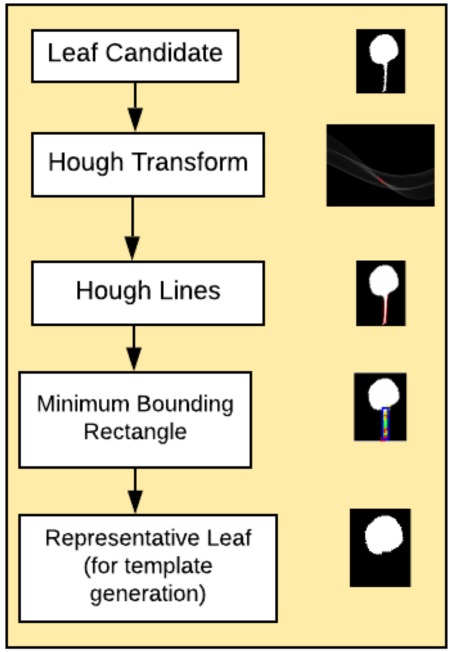
- The instances are rotated for a vertical orientation and is used to generate a flip image w.r.t this medial axis (joining the end points). Then, the similarity between these images in terms of affine cost is used to select the candidate leaf shapes [17].
- The threshold value on this affine cost results in the selection of non-occluded leaf instances.
- The motivation behind extracting the no-occluded leaf instances is to utilise their shape information in the form of templates. The templates generated from these instances is further utilised to extract the leaf instances from the occluded regions of the plant canopy.



(a) (b) (c)

Proposed Framework

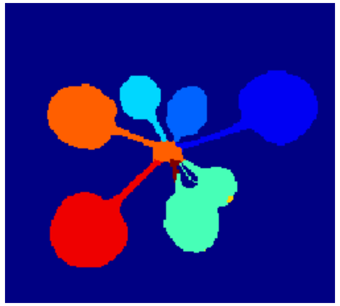
- A post-processing pipeline to remove stems based on Hough transform [18] is utilised.



- These representative shapes from sampled images are then used for template generation.

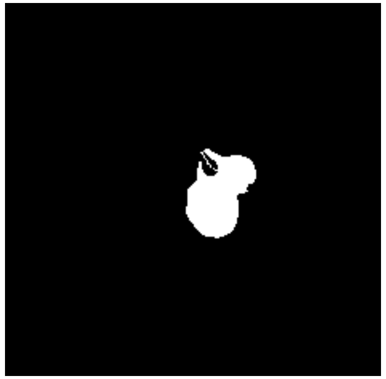
Results

Random Walk Instance Output



Leaf Instance selected based on symmetry test

Modified Mask



Multi-Leaf Template Matching

Method	SBD(%)	DiC
IPK	74.2	-1.9
Nottingham	68.0	-3.6
Wageningen	72.8	0.4
MSU	78.0	-2.3
Proposed framework	**74.7**	**-2.5**


thank you

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