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Image Based Plant Phenotyping using Graph Based Method and Circular Hough Transform

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Image based plant phenotyping plays a vital role in productive and sustainable agriculture. It is used to record plant growth, chlorophyll fluorescence, yield, width and tallness of plants and leaf area, frequently and accurately. Among these characteristics, plant growth is an important characteristic to be analyzed, which directly depends on leaf count. Taking benign conditions of quick advancement in computer vision and image processing algorithms, a new method is proposed to extract the leaves from complex background and to count the number of leaves. The proposed method has two stages. In the first stage, leaf region is separated from the background, using graph based method. In the second stage, leaves are counted by using Circular Hough Transform (CHT). The proposed method is experimented with Leaf Segmentation Challenge (LSC) benchmark datasets. The proposed method achieves the Dice score of 93.2% and FBD of 94.3%, which are higher when compared with the existing recent relevant methods.

Keywords: plant phenotyping, leaf extraction, clustering, circular hough transform, leaf count

1. INTRODUCTION

Plants are the pivotal source of food, fuel, *etc.* So the researchers along with breeding industry are making great efforts to continue agriculture for a long period without any interruptions. Plant phenotyping is a key element in addressing rural necessities without bounds, one of which is expanding crop yield that requires a tremendous amount of research. Image based plant phenotyping is used to predict crop yield by analyzing the plant traits. Many methods have been proposed for the specific acquisition scenarios and the controlled experimental design. Few attempts have been made to create automated software applications for analyzing the plant images. In achieving the goal of increasing the throughput of non-destructive plant phenotyping, different computer vision and imaging techniques are proposed.

A pivotal measure of research is committed to plant phenotyping that comprises research in the field of leaf segmentation, leaf counting, identifying ailments in plants, and examining the growth and development of a plant by analyzing the plant images. The image based plant phenotyping is used to analyze the characteristics of plant growth and development, for estimating the crop yield. Plant growth depends on the total number of leaves [1], hence the leaf count measurement will be used for assessing the plant growth.

The plant images may contain numerous leaves, branches, stems, and other objects in the background which meddle with the procedure. The leaf region must be isolated

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from the image, in order to count the leaves accurately. In this paper, a new method based on graph is proposed to extract the leaves from the background, with minimum manual interaction and to count the number of leaves.

2. LITERATURE SURVEY

Nowadays, plant phenotyping takes place in the green house, the controlled laboratory environment, or in the field. Many researchers have contributed to plant phenotyping. Manuel Grand-Brochier *et al.* [2] portrayed the studies, in view of various segmentation methods applied for extracting tree leaves from natural images. Y. J. Huang *et al.* [3] presented an approach for identifying plant species automatically. Several leaf segmentation systems [4] use shapes as the feature, for segmentation. Few systems use depth or infrared information [5] for segmentation. Xiaodong Tang *et al.* [6] developed an algorithm for extracting the leaves, from the images with complex background.

Yin *et al.* [7] used Chamfer derived energy function to match the available segmented leaf templates, with unseen data for arabidopsis leaf segmentation and tracking. Dellen *et al.* [8] used a graph-based method to segment and track leaves of tobacco plants. Aksoy *et al.* [9] derived superparametric clustering to track the leaves over time. De Vylder *et al.* [10] used active contour to segment and track the leaves of arabidopsis. Wei-Zheng Shen *et al.* [11] developed an automated counting soybean leaf aphids system based on computer vision technology. Miao Jiang and Yi Lin [12] proposed a multistep method for the recognition of individual deciduous trees in leaf-off aerial ultrahigh spatial resolution remotely sensed (UHSRRS) imagery. Cerutti *et al.* [13] proposed a parametric active polygon model. The drawbacks of these methods are (i) the requirement of large labeled datasets and prior training; (ii) incapable of handling occlusions; (iii) requirement of post processing for complete plant segmentation.

Wu and Nevatia [14] proposed a method for multiple and partially occluded objects detection and segmentation. Rosette Tracker software [15] is an open source tool to quantify the genotype effects. gPb-owt-ucm [16] is a segmentation method that depends on contour detection and spectral clustering. Maximal Similarity Based Region Merging (MSRM) [17] is an interactive segmentation approach, in which super-pixel segmentation is fused based on region merging framework.

In segmentation via 3D histogram (Seg_3D) method [18], 3D histogram cubes are used for supervised foreground/background segmentation. Seg_3D method uses leaf centre points, leaf split points, distance map and skeleton for finding the individual leaf. In Simple Linear Iterative Clustering (SLIC) superpixels segmentation (Seg_SLIC) method [18], SLIC superpixel is used for segmentation. This method does not require training. To extract the whole plant, superpixel over-segmentation in L^*a^*b color space is done using SLIC. In the superpixel space, simple seeded region growing is used for foreground extraction. This method uses distance map, superpixels and watershed transform for identifying the individual leaves.

Leaf segmentation with Chamfer matching (Seg_chamfer) method [18] is originally applied in plant fluorescence videos for segmenting and tracking leaves. This method involves in generation and matching of set of templates with different shapes, scales, and orientations to find the individual leaves. The leaf segmentation with watersheds (Seg_ watershed) method [18] comprises two stages: In the first stage, plant is segmented from the background using supervised classification along with neural network. In second stage, individual leaf is identified by applying watershed method on Euclidean distance map of the resulting plant mask image of the plant segmentation stage.

In Seg_chamfer method, segmentation accuracy depends on the number of templates created. More templates have to be created, if there is a large difference in shape and size of leaves which is very difficult. In Seg_watershed method, the dataset is trained. The throughput of the system directly depends on the training. Therefore, proper training has to be done in order to get more segmentation accuracy. In Seg_SLIC method, the accuracy depends on the selection of superpixels. To overcome these drawbacks of the systems, a new method has been developed using graph based approach and circular hough transform (CHT).

3. PROPOSED WORK

The proposed method is designed carefully to work automatically with minimum user interaction without affecting the generalization of the method and accuracy. Fig. 1 shows the steps involved in extracting the leaves from background and counting the total number of leaves. The proposed method consists of two steps: Leaf extraction and leaf count.

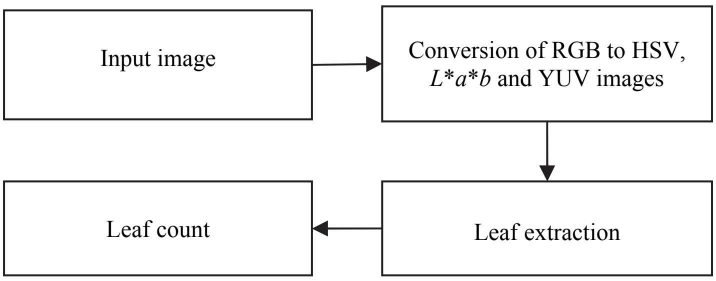


Fig. 1. Process of leaf extraction and leaf counting.

3.1 Leaf Extraction

Leaf extraction (segmentation) is an essential step for plant leaf classification, plant species identification, automatic feature extraction, *etc.* Leaf extraction is an exigent problem, when the background images are complex in nature. Leaves of different plants show various shapes and structures. Few plant species have compound leaves and a few others have clustered leaves (*e.g.*, Pine). Region based or edge based segmentation methods are difficult to use in extracting the leaves having complex boundaries. Color based pixel wise method performs better than these methods. Recent methods for leaf recognition [19] rely on the Expectation-Maximization (EM) algorithm for separating the background and foreground pixels. Regardless of their efficiency, robustness to reflections and shadows are not assured which leads to incorrect boundaries. In this paper, the proposed work uses graph based method to extract the leaves from complex background.

In the proposed graph based method, HSV, $L*a*b$ and YUV color spaces are used to calculate the edge cost of the graph. There are two phases in the proposed graph based leaf extraction: (i) Graph construction and (ii) Leaf segmentation.

(A) Graph construction

A graph $G = (V, E)$ is constructed (shown in Fig. 2) for the given image, where $v_i \in V$ denotes the pixels of the image and an edge $(v_i, v_j) \in E$ connects the pixels v_i and v_j. There are two types of edges: (i) edges connecting a pair of neighboring pixels and (ii) edges connecting terminal (source or sink) and a pixel. All the edges in the graph are assigned to a weight or cost. In this proposed work, the edge weights or edge costs (w_{si}, w_{ij} and w_{it}) are calculated as follows:

Let

$$\Theta_H = \{x: \tau_{H\_\min} \leq x \leq \tau_{H\_\max}\} \tag{1}$$

$$\Theta_S = \{x: \tau_{S\_\min} \leq x \leq \tau_{S\_\max}\} \tag{2}$$

$$\Theta_Y = \{x: \tau_{Y\_\min} \leq x \leq \tau_{Y\_\max}\} \tag{3}$$

$$\Theta_a = \{x: \tau_{a\_\min} \leq x \leq \tau_{a\_\max}\} \tag{4}$$

be the parameters used in the graph construction, whose values are discussed in section 5.

$$T_i = \begin{cases} \text{true, when } H(v_i) \in \Theta_H \wedge S(v_i) \in \Theta_S \wedge Y(v_i) \in \Theta_a \\ \text{false, otherwise} \end{cases} \tag{5}$$

where $H(v_i)$, $S(v_i)$, $Y(v_i)$ and (v_i) are the 'H', 'S', 'Y' and '$*a$' values of pixel v_i in the HSV, YUV and $L*a*b$ color spaces.

$$w_{si} = \begin{cases} 0, & \text{if } T_i \text{ is true} \\ 1, & \text{otherwise} \end{cases}, \tag{6}$$

where T_i is the edge cost prediction parameter for pixel v_i (designated as the intermediate node of the graph), w_{si} is the edge cost between source node 's' and intermediate node v_i.

$$w_{ij} = \begin{cases} 0, & \text{if } T_i \wedge T_j \text{ is true} \\ 1, & \text{otherwise} \end{cases}, \tag{7}$$

where T_i and T_j are the edge cost prediction parameters for pixels v_i and v_j, w_{ij} is the edge cost between intermediate neighboring nodes v_i and v_j.

$$w_{it} = \begin{cases} 1, & \text{if } T_i \text{ is false} \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

where w_{it} is the edge cost between intermediate node v_i and sink node 't'.

Eqs. (1)-(8) are used to construct the graph for segmenting the leaf region of the given plant image.

(B) Leaf segmentation

After constructing the graph of the plant image (as shown in Fig. 2), a graph based algorithm (Algorithm 1) is used to find the walk efficiently for segmenting the leaf region from the background. The walk starting from the source node for segmenting the leaf region may be a closed walk or open walk. Two search trees (*S* and *T*) are built, one from the source node(s) and the other from the sink node (*t*), for detecting the leaf region and non-leaf region respectively. The nodes in the search trees S and T represent the leaf region and the non-leaf region of the plant image respectively. In the proposed method, these trees are reused for segmentation without starting from the source node or sink node, when there is an existence of equal weighted adjacent edges connecting the internal nodes (except source and sink).

The nodes present in the search tree *S* can be either "leaf_border" or "leaf_non_border" nodes. In the search tree *S*, the leaf_border nodes represent the leaf boundary, while the leaf_non_border nodes represent the internal leaf region. The leaf_border nodes explore neighbor edges and make the neighbor nodes to a leaf_border node of the corresponding search trees.

Similarly, the search tree *T* has two types of nodes: "non_leaf_border" node and "non_leaf_non_border" node, which represent the boundary of the background (non-leaf) and the background internal region. The nodes in search tree *S* represent the leaf region and the nodes in search tree *T* represent the non-leaf region. As soon as all adjacent nodes of a given leaf_border node are explored, the leaf_border node becomes leaf_non_border node. A walk is found, when a leaf_border node in the search tree S detects an adjacent node that belongs to the search tree *T*. The algorithm1 describes the graph based leaf segmentation.

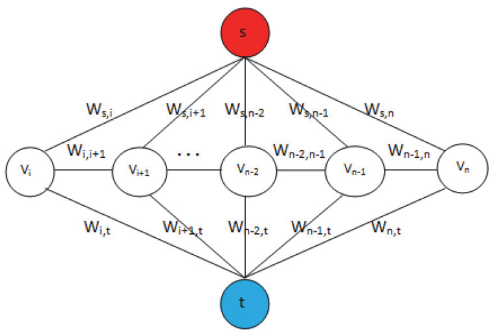


Fig. 2. Efficient Graph based approach for leaf segmentation.

Algorithm 1: Graph based leaf segmentation

1: **procedure** SEGMENT_LEAF (Constructed Graph *G*)
   // Input image is resized to equal number of rows and columns.
2: s = Source_node
3: t = Sink_node
4: v_i = intermediate node
5: $w_{s,i}$ = edge cost between source node 's' and intermediate node v_i.
6: $w_{i-1,i}$ = edge costs between intermediate neighboring nodes v_{i-1} and v_i.

$w_{i,i+1}$= edge costs between intermediate neighboring nodes v_i and v_{i+1}.
$w_{i,t}$ = edge cost between intermediate node v_i and sink node 't'.
n = number of rows × columns of the image.
    Leaf_region = { }
    Non_Leaf_region = { }
    if ($w_{s,1} = 0$)
      Leaf_border node = v_1
      Leaf_region = Leaf_region $\cup$ {v_1}
    else
      Non_leaf node = v_1
    end if
    for i = 2 to n−1
        if ($w_{i-1,i} = 0$)
        $w_{i,i+1} = w_{i-1,i} + w_{i,i+1}$
      end if
        if ($w_{i,i+1} = 0$)
if ($w_{i+1,t} = 0$)
            Leaf_border node = v_{i+1}
            Leaf_region = Leaf_region $\cup$ {v_i, v_{i+1}}
          else
            Non_Leaf_region = Non_Leaf_region $\cup$ {v_{i+1}}
            $w_{i,i+1} = 0$
          end if
        end if
    end for
end procedure

3.2 Leaf Count

In this phase, all leaves in the image should be identified. For each leaf, the objects other than leaves like branches, stems, *etc.* must be removed. These steps can be done by using opening morphological operation [20]. As a result, the regions of leaves are extracted from the plant images. Since the leaves in Arabidopsis dataset are mostly round in nature, Circular Hough Transform (CHT) [20-23] is used for counting the leaves.

CHT identifies the circular patterns in the image. It is easy to show that there is a common intersection point for the curves corresponding to collinear points. This intersection point characterizes the line passing through these collinear points. This portrays that the problem of finding the collinear points becomes the problem of finding the concurrent curves. Thus, CHT becomes the modified versions of Hough Transform. In CHT, feature points in the image space are transformed to accumulated votes in a parameter space. Then, for all combinations of parameters, votes are collected in an accumulator array (3D_H_Array(x_0, y_0, r)) for each feature point. The array elements, which have highest number of votes, denote the presence of circle.

The CHT algorithm has two stages. The first stage involves in identifying the center (c) of the circle, while the second stage involves in identifying the radius of the circle using histogram. There is a constraint that the normal vectors to boundary of the circle must intersect at the center of the circle. This is used to locate the center of the circle. These normal directions can be found by edge detection operators. Most of these lines intersect at certain point, whose coordinates acts as the coordinates of circle center.

The second stage can be considered similar to one dimensional Hough Transform. The radius of the circle can be identified by finding histogram for $\delta = (x - x_0)^2 + (y - y_0)^2$ where (x_0, y_0) are the coordinates of the circle center (c) identified in the first stage of the algorithm. The largest peak in the δ histogram acts as the radius of the circle.

The outcomes of the leaf extraction phase serves as the input for leaf counting phase. Convert this extracted leaf region into binary image. Apply CHT on this binary image. Individual leaves are recognized, based on the circular portion of the leaves. The total number of leaves is given by counting the leaf center.

The following steps are used in counting the number of leaves.

Step 1: Convert the extracted RGB colour leaf image to grayscale leaf image.
Step 2: Find the normal vectors $(v_1, v_2, \ldots, v_n)$ to boundary of each leaf.
Step 3: $c(x_0, y_0)$←maximum number of vectors $(v_1, v_2, \ldots, v_n)$ intersect at particular point.
Step 4: Find the histogram for $\delta = (x - x_0)^2 + (y - y_0)^2$
Step 5: r←histogram_peak ($\delta = (x - x_0)^2 + (y - y_0)^2$)
Step 6: Create 3D Hough array 3D_H_Array(x_0, y_0, r).
Step 7: Apply edge detection operator (Canny [24]) to detect edges.
Step 8: For each pixel in the image
        If (pixel=edge_pixel) then
            Increment the corresponding elements in the Hough array 3D_H_Array(x_0, y_0, r)
        End If
    End For
Step 9: Find highest count in elements of 3D_H_Array(x_0, y_0, r).
Step 10: Coordinates of center of the circles ($c(x_0, y_0)$) in the image←Coordinates with the highest count in 3D_H_Array(x_0, y_0, r).
Step 11: Leaf count←count($c(x_0, y_0)$).

As a result of these two phases, identifying leaf region and counting the number of leaves in plant images are done automatically with minimum user interaction.

4. DATASET DESCRIPTION

The datasets (A1, A2, A3) used in our experiment to evaluate the proposed work are the benchmark datasets [25] for Leaf segmentation challenge, which are the images of group of plants arranged in trays. The datasets A1 and A2 consist of time-lapse and top-view images of many Arabidopsis which are arranged in trays. As per the researchers [25], these images were captured only during day time for 3 weeks in every 6 hour for dataset A1, and for 7weeks in every 20min for dataset A2 using a 7 MP Canon PowerShot SD1000 camera. The raw images (3108×2324 pixels, pixel resolution of ~0.167mm) acquired were saved as uncompressed (TIFF) files, and encoded using the PNG file format lossless compression standard. A3 consist of images of tobacco plants.

A1 offers a complex and changing background. A2 offers a simpler scene. A3 has high image resolution. There are 128 (500×530 pixels), 31 (530×565 pixels), and 27 (2448×2048 pixels) images for A1, A2, and A3 respectively. A variety of plant images at various growth stages are included in the datasets. A1, A2, and A3 consist of images of isolated plants and group of plants. The images in the datasets vary in resolution, scene complexity and fidelity. Due to the different scene complexities and the presence of plant objects, the datasets provide many challenges with respect to analysis. Images corresponding to different challenging situations are included in the datasets.

In A1 and A2, the presence of irrigation water in tray causes reflections. When the plant grows, the overlapping of leaves occurs, which results in leaf occlusions. There are changes in sizes and shapes from one time to another, due to nasty movements of leaves. In A3, apart from nasty movement changes, the leaf shapes are different due to various treatments. One of the treatments includes high and low illumination condition. Under high illumination condition, plants become more compact with overlapping and partly wrinkled leaves. Under low illumination condition, leaves become large and round.

In A1 dataset, Arabidopsis images have complex and changing background, which produce more complication in plant segmentation. The changing and complex background scene includes slightly out of focus scene which appears blurring, and a few images contain external objects like markers or tape. The presence of moss on the soil in certain pots or having yellowish dry soil increases the complication in segmentation. The A2 dataset images show simpler scene with sharper focus, more uniform background and without moss. However, it includes different phenotypes mutants of Arabidopsis related to rosette plant size and different appearances in terms of leaf shape and size. The tobacco images in A3 dataset have high resolution, which produces computational complexity. The factors like leaf colour variation, shadows, self-occlusion, and leaf hairs make the scene even more complex.

5. RESULTS AND DISCUSSIONS

In this research, LSC benchmark datasets A1, A2, A3 and whole tray plant images with varying complexities have been used for experimentation. The proposed method is implemented in Matlab (release 2012b) on a laptop equipped with Intel Core 2 Duo processor, 2.0 GHz speed and maximum of 4 GB memory, running on 32-bit Windows operating system. On average, each image of A1 and A2 datasets takes approximately 2 seconds and approximately 10 seconds for each image of A3 dataset. The time complexity of the proposed algorithm is $O(n)$ where 'n' is the number of rows × columns of the image.

In the existing works, the authors have used different metrics to evaluate the performance of their works. The metrics used are (i) Foreground–Background Dice (FBD%) to evaluate extracted plant delineation with respect to ground truth; (ii) Difference in Count (DiC) to find the difference in number of leaves between algorithm's result and ground truth; (iii) Absolute value of DiC (|DiC|); (iv) Dice score (Dice%), which is given in Eq. (9) used to measure the spatial overlap between algorithmic result and ground truth; (v) Precision, given in Eq. (10) used to find the fraction of segmented image pixels that matches with the ground truth; (vi) Recall, given in Eq. (11), used to find the fraction of ground-truth pixels present in the segmentation image and (vii) Jaccard, given in

Eq. (12), used to measure the spatial overlap between algorithmic result and ground truth.

$$dice(\%) = ((2\times TP)\div(2\times TP)+FP+FN))\times 100 \quad (9)$$
$$precision(\%) = (TP\div(TP+FP))\times 100 \quad (10)$$
$$recall(\%) = (TP\div(TP+FN))\times 100 \quad (11)$$
$$jaccard(\%) = (TP\div(TP)+FP+FN))\times 100 \quad (12)$$

where True Positive (TP), False Positive (FP) and False Negative (FN) represent the number of correctly identified leaf pixels, number of falsely identified leaf pixels and the number of unidentified leaf pixels, respectively.

In the paper [18], FBD% is used to measure the segmentation accuracy and DiC is used to find the leaf count accuracy. But, the authors in the research works [15, 16] have used Dice, Precision, Recall and Jaccard to measure the segmentation accuracy. So, different metrics have been used to measure the segmentation accuracy. In the proposed work, all these metrics are used to evaluate the performance.

The performance of the proposed method is influenced by H component and S component of HSV image, Y component of YUV image and $*a$ component of $L*a*b$ image. H, Y and $*a$ are used to identify the green leaf region. S component of HSV image is used to differentiate the leaf region from the reflection of light in the tray. In our experimentation, for all datasets (A1, A2, and A3), a common parameter value is used for H, S, Y and $*a$. The values of the parameters used in Eqs. (1)-(4) for constructing the graph are chosen empirically. For datasets A1, A2, and A3, the normalized parameter value for H ($\mathcal{T}_{H\_min} = 0.2$, $\mathcal{T}_{H\_max} = 0.4$), for S ($\mathcal{T}_{S\_min} = 0.3$, $\mathcal{T}_{S\_max} = 1$) and the un-normalized parameter value for Y ($\mathcal{T}_{Y\_min} = 75$, $\mathcal{T}_{Y\_max} = 255$), for *a ($\mathcal{T}_{a\_max} = 108$, $\mathcal{T}_{a\_max} = 128$) are chosen. Tuned parameter values for H and Y have also been used in our experimentation for individual dataset to improve the accuracy. The tuned parameter values for H are ($\mathcal{T}_{H\_min} = 0.2$, $\mathcal{T}_{H\_max} = 0.4$), ($\mathcal{T}_{H\_min} = 0.17$, $\mathcal{T}_{H\_max} = 0.4$) and ($\mathcal{T}_{H\_min} = 0.2$, $\mathcal{T}_{H\_max} = 0.4$) for A1, A2, and A3 datasets respectively. The tuned parameter values for Y are ($\mathcal{T}_{Y\_min} = 85$, $\mathcal{T}_{Y\_max} = 255$), ($\mathcal{T}_{Y\_min} = 65$, $\mathcal{T}_{Y\_max} = 255$) and ($\mathcal{T}_{Y\_min} = 25$, $\mathcal{T}_{Y\_max} = 255$) for A1, A2, and A3 datasets respectively. Fig.3 shows the tuned parameter values used in the experiment will increase the accuracy of leaf extraction phase. Therefore, the tuned parameter values are preferred to extract the leaf region from the background. The figures (Figs. 4-11) show the experimental results on plant images with varying complexities.

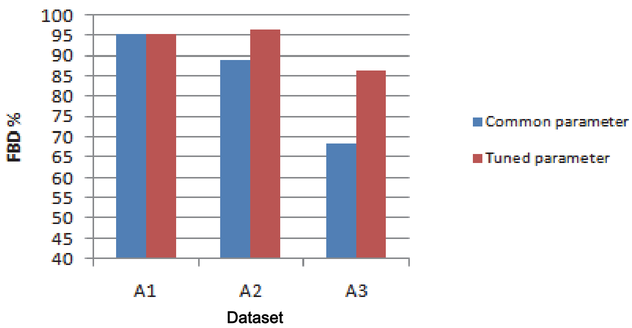
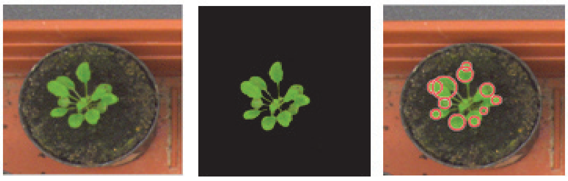
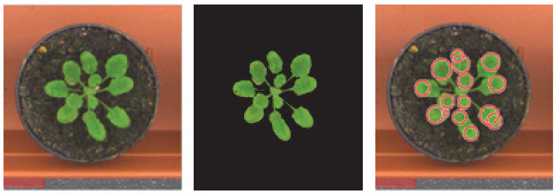


Fig. 3. The dataset-FBD% graph obtained for different parameters: Common parameter and tuned parameter.



Original image Leaf extraction Leaf identification

Fig. 4. Identification of Leaves in a plant image from dataset A1.

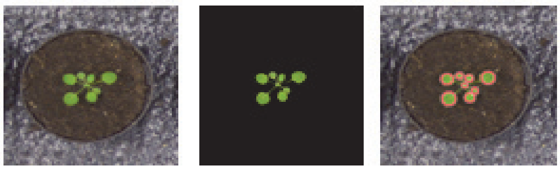


Original image Leaf extraction Leaf identification

Fig. 5. Identification of Leaves in a plant image from dataset A1.

Original image Leaf extraction Leaf identification

Fig. 6. Identification of Leaves in a plant image from dataset A1.

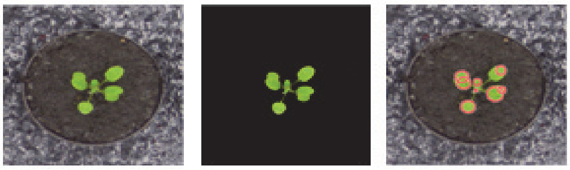


Original image Leaf extraction Leaf identification

Fig. 7. Identification of Leaves in a plant image from dataset A2.

Original image Leaf extraction Leaf identification

Fig. 8. Identification of Leaves in a plant image from dataset A2.

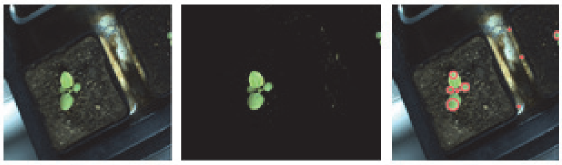


Original image Leaf extraction Leaf identification

Fig. 9. Identification of Leaves in a plant image from dataset A2.

Original image Leaf extraction Leaf identification

Fig. 10. Identification of Leaves in a plant image from dataset A3.



Original image Leaf extraction Leaf identification

Fig. 11. Identification of Leaves in a plant image from dataset A3.

The proposed method is compared with Seg_SLIC method [18], Rosette Tracker [15] tool and the existing segmentation algorithms [16, 17, 26, 27]. Table 1 shows the comparison of proposed method with the Seg_SLIC method. The proposed method shows better performance than Seg_SLIC method, in terms of both segmentation and leaf counting accuracy. The proposed method achieves overall segmentation accuracy of 94.3%, which is higher than the Seg_SLIC method.

Table 1. Segmentation and Leaf counting results.

Method	FBD %	$\lvert DiC \rvert$	DiC
Seg_SLIC (2016)			
A1	94.6 (1.6)	3.8 (2.0)	−3.6 (2.4)
A2	87.5 (19.7)	2.5 (1.5)	−2.5 (1.5)
A3	79.4 (34.5)	2.3 (1.8)	−2.3 (1.9)
ALL	91.2 (16.2)	3.4 (2.0)	−3.2 (2.2)
Proposed			
A1	95.5 (3.1)	2.0 (1.8)	−0.9 (2.5)
A2	96.3 (2.3)	3.8 (5.9)	1.2 (4.7)
A3	86.5 (17.3)	2.4 (4.7)	0.8 (4.1)
ALL	**94.3** (7.8)	**2.4** (3.8)	**0.3** (2.9)

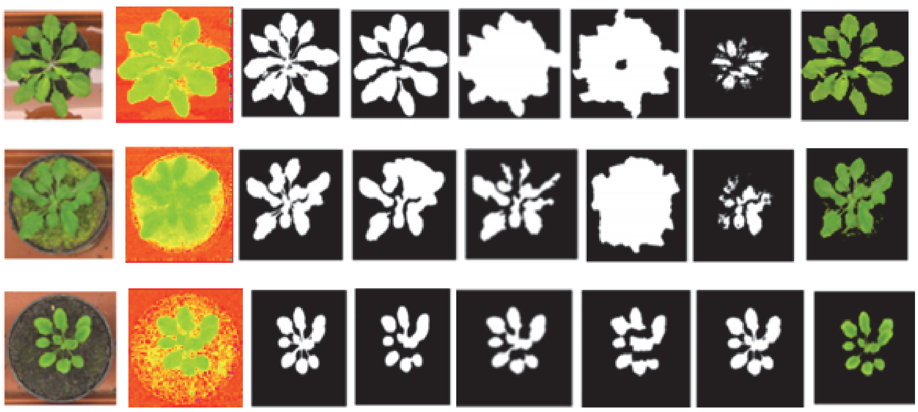
Table 2 shows the comparison of the proposed method with Hierarchical Image Segmentation (gPb-owt-ucm) method [16] and Rosette Tracker [15]. Overall, the segmentation accuracy (Dice-93.2%) of our proposed method is higher. The proposed method shows less standard deviation (shown in bracket) compared to other methods, implies that it performs equally well for most of the images in the dataset and thus maintaining the robustness of the system.

Table 2. Segmentation results.

Method/Tool	Accuracy (%)			
	Precision	Recall	Jaccard	Dice
gPb-owt-ucm	89.04(6.40)	96.20(2.78)	85.86(5.49)	92.29(3.36)
Rosette Tracker	88.86 (6.49)	78.83 (24.37)	71.20 (22.29)	80.37 (22.57)
Proposed	93.7 (2.09)	92.8 (2.54)	87.3 (1.15)	**93.2 (0.66)**

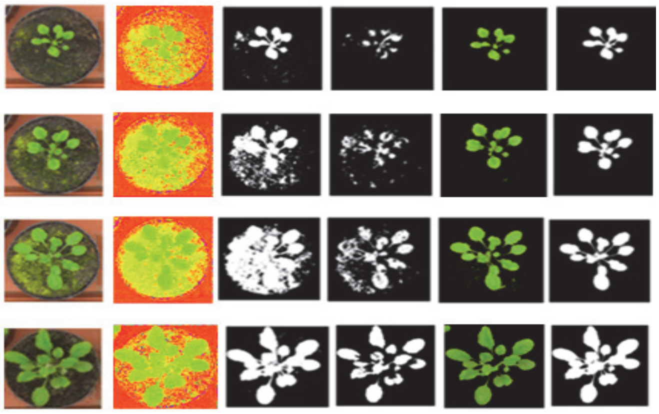
The proposed method is also visually compared with different existing segmentation algorithms such as segmentation using contour detection and Hierarchical Image Segmentation (gPb-owt-ucm) [16], Maximal Similarity Based Region Merging (MSRM) [17], Cosegmentation via Submodular optimization on anisotropic diffusion (CoSand) [26] and Saliency Detection method by combining Simple Priors (SDSP) [27]. The results are shown in Figs. 12 and 13.

The figures (Figs. 12 and 13) show that the proposed method shows high segmentation accuracy than these segmentation methods applied in plant phenotyping, for extracting the leaves from background. The proposed method is also compared with the plant phenotyping tool 'Rosette Tracker' with tray images as input images, as shown in Fig. 14. It is clearly visible from the figures (Figs. 13 and 14) that over segmentation occur in Reference method, under segmentation occur in Rosette Tracker and the segmentation result of the proposed method is closer to the ground truth image. The hue map of the input image is also included in Figs. 12-14.



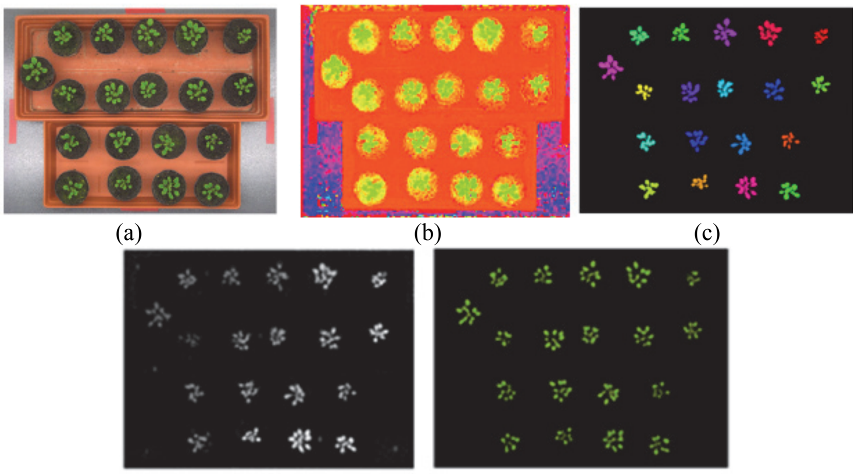
(a) (b) (c) (d) (e) (f) (g) (h)

Fig. 12. Example segmentation results of various methods; (a) Original image; (b) Hue map; (c) ground truth; (d) gPb-owt-ucm (2011); (e) MSRM (2010); (f) CoSand (2011); (g) SDSP (2013) and (h) proposed method.



(a) (b) (c) (d) (e) (f)

Fig. 13. Example segmentation results of various methods; (a) Original image; (b) Hue map; (c) Reference; (d) Rosette Tracker; (e) Proposed method and (f) Ground truth.



(a) (b) (c)

(d) (e)

Fig. 14. Example segmentation results of various methods; (a) Original image; (b) Hue map; (c) Ground truth; (d) Rosette tracker and (e) Proposed method.

6. CONCLUSION

A new graph based method for plant segmentation in image based phenotyping is proposed. This method relies on the graph algorithm, color features and circular hough transform. The experimentations are carried out and evaluated by using common parameter values as well as tuned parameter values. The proposed method is compared with existing methods and tools. The proposed method achieves the Dice score of 93.2% (for tray images), which is higher than the existing methods or tools and it also achieves the FBD of 94.3% (for datasets A1, A2, A3), which is higher than the Seg_SLIC method.

The proposed method can be commonly used to extract leaves not only in rosette plants but also in all plants having green leaves. Leaf counting procedure is applicable to all the plants having round or elliptical shaped leaves. The overall efficiency of the proposed method will show dramatic increase in leaf extraction and leaf counting, when the leaves are green in colour and round in nature. The usage of this proposed method in plant phenotyping can be increased in future, by converting our method as an open source.

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