Plant Leaves Region Segmentation in Cluttered and Occluded Images Using Perceptual Color Space and K-means-Derived Threshold with Set Theory

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***Abstract*—Current techniques on plant leaves segmentation have different levels of design complexities with potential excellence as well as drawbacks. In this paper, we propose an hybrid approach which combine the discriminatory power of color-based technique with the simplicity of threshold-based technique. There are three successive stages in the proposed method. First, copy of the threshold-derived binary image undergoes infinitesimal angular displacement. Second, rotation transformation disturb the boundary of plant leaves region and weaken cluttering and occluding objects. Finally, the application of set theory to the stationary and displaced binary images allows the simultaneous detection of leaves boundary pixels and the elimination of clutters and occluding objects. Comparative performance evaluation with selected state-of-the-art techniques shows that the proposed method demonstrate strong robust features and computational efficiency.**

***Index Terms*—plant leaves, k-means clustering, color space, clutter, occlusion, set theory**

I. Introduction

Plant segmentation is the process of classifying an image into plant and non-plant pixels. Information obtained from plant segmentation has numerous applications. They include deriving the phenotypic traits of plants [1], 3D plant modeling [2], estimating leaves movements under varying illumination conditions [3], [4], plant classification for plant inspection and plant specie identification [5] and plant leaves detection for autonomous weed control [6].

Several challenges makes plant segmentation a nontrivial image analysis task. Presence of weeds including moss in the soil act as clutters in the acquired image. Plant monitoring and inspection tasks which requires image acquisition at different seasons of the year generate images with different levels of fidelity, scene complexities and resolutions. Tapes and markers used for monitoring plant growth will act as clutters and occluding objects if captured during image acquisition. Occlusion may also be caused by overlapping growing plant stems and plant leaves.

Current approaches to plant segmentation algorithms can be categorized into color-index, threshold and machine learning techniques [7]. Color-based approaches transform images acquired in the RGB color space to a color space that provides higher discrimination between plants and background pixels. Contributions in this category include [8], [9], [10]. The most recent contribution [10] transforms the image to the HSV color space, followed by image enhancement and the application of graph based method to extract leaves region. An earlier contribution [8] transform the RGB image to the CIELAB color space. Thereafter, a fixed number of superpixels are computed over the color transformed image for the extraction of the plant leaves.

Threshold-based techniques apply global threshold on color space transformation of the original image to automatically classify the image into the target object and the background pixels. Otsu method [11] is the most popular threshold-based technique, but it exhibit shortcomings in several applications. Several modifications of Otsu methods and several threshold methods such as [12] and [13] have been proposed to overcome the drawbacks of Otsu method.

Learning-based techniques build a mathematical model from sample data to make predictions without being explicitly programmed to perform the task [14]. Learning based approaches can be classified into supervised and unsupervised learning. In supervised learning, an algorithm utilize training data to learn a mathematical model. In unsupervised learning, there is no training data, but there is still learning. The learning comes from modeling the underlying distribution in the available data. Contributions on learning.based techniques include [15], [16].

Review of the literature shows that there is no technique or contribution that can be universally applied to plant segmentation. The performance of color-based and threshold-based technique can be limited by low quality images acquired under severe weather condition such as snow fall, rain fall and poorly illuminated environments. A major drawback of global threshold method is that the accuracy of the segmentation is strongly dependent on accurate determination of the global threshold. It is very challenging to compute the global threshold of images in the presence of structural and color variations. Learning-based methods which are designed to overcome the draw backs of color and threshold techniques has several shortcomings. Its performance is dependent on large volume of data, which is not always available. The design of learning-based technique can be expensive, time consuming and requires close monitoring. There is no limit to the size and extent of training data and it can take very long time for the algorithm to attain acceptable level of performance.

In this report we propose a new hybrid approach for plant segmentation. Our approach combine the discriminatory power of color-based technique with the simplicity of threshold-based technique. Rotation transformation applied to the output of the thresholding step disturb pixels that describe the boundary of plant leaves as well as weaken background clutters and occluding objects. Application of set theory allows simultaneous detection of plant boundary pixels and the elimination of cluttering and occluding objects. Comparative performance evaluation show that the proposed method is robust, computationally efficient and comparable to current state-of-the-art plant segmentation algorithms.

II. Materials and Methods

A. Sources and Description of Data

Data used for this study were obtained from the computational vision database of the California Institute of Technology (CALTECH) http://www.vision.caltech.edu/archive.html and the Leaf Segmentation Challenge (LSC) https://www.plant-phenotyping.org/CVPPP2014-dataset.

The data from CALTECH contain 186 images from 3 species of plant leaves. Each image is of size 896 x 592 pixels and contain single leaf against different background clutters. The data from LSC are benchmark datasets for studying the phenotypic traits in plants [17]. In this study we utilized only the dataset tagged A1 because it contains more images that are challenging with respect to image analysis than the combination of the other two datasets, A2 and A3. The A1 dataset contain 128 time-lapse Arabidopsis plant images arranged in circular trays. The dimension of each image is 500 x 530 pixels. The images were used to study how plants leaves grow in changing and complex background scenarios. Some of the images have scenes of specular reflections due to the presence of irrigation water in the tray. There are also growth induced occlusions from overlapping leaves as well as clutters formed by yellowish dry soil, presence of markers, tapes and moss in the soil.

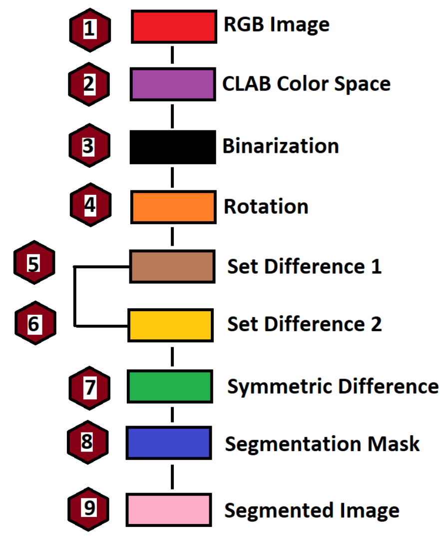

Fig. 1. The 9 implementation steps for plant leaves segmentation in cluttered and occluded environments (1) original RGB image is converted to (2) a color channel in the CIELAB color space. The color channel image is transformed to the (3) binary domain using global threshold derived from k-means clustering. (4) The binary image, after undergoing infinitesimal angular displacement. (5) Set difference between the stationary binary image and the displaced binary image. (6) Set difference between the displaced binary image and the stationary binary image. (7) Symmetric difference image. (8) The segmentation mask. The nonzero pixels in the symmetric difference image are applied to the stationary binary image to eliminate clutters and occluding objects and determine the boundary of the plant leaves (9) The segmentation mask is applied to the original RGB color image to produce the segmented plant leaves.

B. Proposed Plant Leaves Segmentation

The proposed method for plant leaves segmentation is based on the method proposed for skin lesion segmentation in [18].

The flow chart in Fig. 1 and the images in Fig. 2 explains the 9 consecutive stages to implement the proposed method.

1) Reading the Original image
The image shown in Fig. 2a was originally acquired in the RGB color space. It has CALTECH identification number (ID) image_0052.jpg. The test image is read by the algorithm.
2) Color space Transformation
Converting RGB image to grayscale values does not always produce good segmentation results because plant and soil background pixels have similar grayscale values [19]. For this reason, we transform the test image to a color space which satisfies the perceptual uniformity property and can potentially discriminate the leaves from the soil, clutters and occluding objects.
3) Binarization by Kmeans-based Global Threshold
There are five steps to convert the CIELAB channel image to a binary image. In the first step, the image in the new color space, is partitioned into a fixed number $\{K|k = 1, 2, \cdots, K\}$ of clusters using kmeans clustering algorithm [20]. For this study we set $K = 3$, where $k = 1$, represent the plant leaves class, $k = 2$ is the class for the soil and $k = 3$ is the class representing

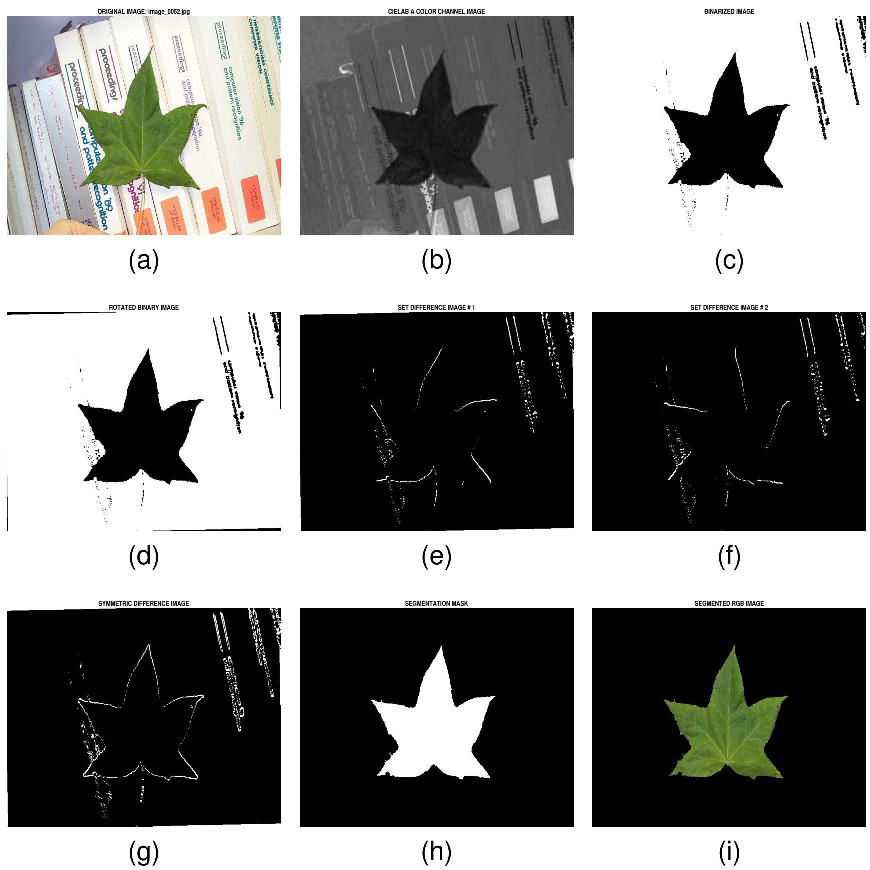

Fig. 2. (a) Plant leaf in a cluttered and occluded environment. The leaf has CALTECH computer vision leaf database ID image_0052.jpg (b). The leaf in (a) is transformed to a color channel in the CIELAB color space (c) Binary image of the image in (b). (d) 1 degree angular displacement image of (c). (e) Image derived from the set difference between the stationary binary image (c) and the displaced binary image (d). (f) Image derived from the set difference between the displaced binary image in (d) and the stationary binary image in (c). (g) Image derived from the symmetric difference between the images in (e) and (f). (h) Segmentation mask built from the symmetric difference image after a single iteration. (i) The segmented plant leaf.

clutters and occluding objects. The second step is to find the center C_k of each kmeans cluster. In the third step, the centers of the clusters are sorted in ascending order. The reasoning here is based on the knowledge that the plant leaves will belong to the clusters with the least centers. The global threshold T_g is set as:

$$T_g = \frac{C_1 + C_2}{2}$$

where C_1 is the cluster center with the least pixel value and C_2 is the cluster center with the least cluster center following C_1. In the fourth step, global threshold is applied to derive a binary image I_{bw}. The last step is to compute the complement I^{C}_{bw} of the binary image shown in Fig. 2c.

4) Rotation Transformation
We make a copy of I^{C}_{bw} and displace this copy through a very small angle δ. The original copy I^{C}_{bw} in Fig. 2c is regarded as the stationary image. The image I^{C}_{bwR} in Fig. 2d was displaced through 1 degree. Infinitesimal angular displacement disturb pixels in the leaves boundary region and severely weaken cluttering and occluding objects.

5) First Set Difference
We now compute the set difference between the stationary and rotated image:

$$(I^{\mathsf{C}}_{bw} \setminus I^{\mathsf{C}}_{bwR}) = \{x | x \in I^{\mathsf{C}}_{bw} \wedge \notin I^{\mathsf{C}}_{bwR}\} \qquad (1)$$

The set difference consists of pixels in a specific location in the stationary image but are not in the same corresponding pixel location in the displaced image. The first set difference image is shown in Fig. 2e.

6) Second Set Difference
In this step we compute the set difference between the rotated and the stationary image:

$$(I^{\mathsf{C}}_{bwR} \setminus I^{\mathsf{C}}_{bw}) = \{x | x \in I^{\mathsf{C}}_{bwR} \wedge \notin I^{\mathsf{C}}_{bw}\} \qquad (2)$$

The set difference consists of pixels in a specific location in the displaced image but are not in the same corresponding pixel location in the stationary image. The second set difference image is shown in Fig. 2f.

7) Symmetric Difference
We compute the symmetric difference of I^{C}_{bw} and I^{C}_{bwR},

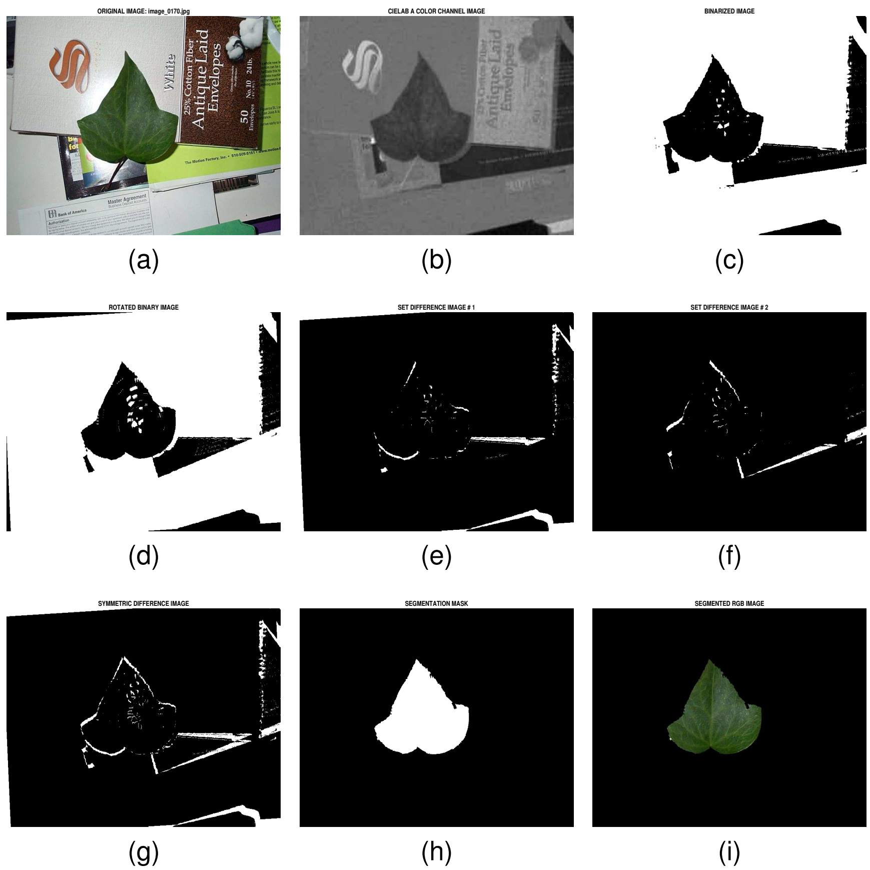

Fig. 3. (a) Plant leaf in a cluttered and occluded environment (b). The leaf in (a) with CALTECH computer vision leaf database ID image_0020.jpg is transformed to a color channel in the CIELAB color space (c) Binary image of the image in (b). (d) 3 degree angular displacement image of (c). (e) Image derived from the set difference between the stationary binary image in (c) and the displaced binary image in (d). (f) Image derived from the set difference between the displaced binary image in (d) and the stationary binary image in (c). (g) Image derived from the symmetric difference between the images in (e) and (f). (h) Segmentation mask built from the symmetric difference image after 3 iterations of the algorithm. (i) The segmented plant leaf.

expressed by:

$$\begin{aligned}(I_{bw}^{\mathsf{C}} \oplus I_{bwR}^{\mathsf{C}}) &= (I_{bw}^{\mathsf{C}} \setminus I_{bwR}^{\mathsf{C}}) \cup (I_{bwR}^{\mathsf{C}} \setminus I_{bw}^{\mathsf{C}}) \\ &= \{x | x \in (I_{bw}^{\mathsf{C}} \cup I_{bwR}^{\mathsf{C}}) \wedge x \notin (I_{bw}^{\mathsf{C}} \cap I_{bwR}^{\mathsf{C}})\end{aligned} \tag{3}$$

Symmetric difference is the set of elements which are in either of the sets and not in their intersection $(I_{bw}^{\mathsf{C}} \cap I_{bwR}^{\mathsf{C}})$. It measures the cumulative change introduced by the angular displacement of the stationary image. The bright pixels in the symmetric difference image shown in Fig. 2g represents the disturbed boundary pixels of the plant leaves as well as the weakened pixels of clutters and occluding objects.

8) Segmentation mask
The segmentation mask I_S shown in Fig. 2h is derived by replacing corresponding pixel locations in the stationary binary image in Fig. 2c with the bright pixels in the symmetric difference image. After pixels replacement, area threshold is applied to remove small nonleaf structures which may have survived the rotation trasnformation. Nonetheless, all the clutters and occlusions may not be eliminated in a single pass. For this reason, it may be necessary to iterate the algorithm for complete elimination of background pixels.

9) Segmented RGB Image
The segmented RGB image I_{Srgb} shown in Fig. 2i is computed by multiplying each color channel I_r, I_g, I_b of the original image with the segmentation mask, followed by vector summation of each component:

$$I_{Srgb} = (I_r)(I_S) + (I_g)(I_S) + (I_b)(I_S) \tag{4}$$

III. Performance Evaluation and Discussion

Figure 3 illustrate the steps to extract plant leaf region in the test image with ID image_0020.jpg from CALTECH computer vision database. Since the dataset from CALTECH does not have ground truth, each segmented image was visually compared to the original image. Comparison between the segmented images in Fig. 2i and Fig. 3i to their corresponding original images in Fig. 2a and Fig. 3a, respectively, provides insight into the performance of our proposed method. The parameters of the proposed method in the segmentation of the image in Fig. 2i are 1 degree angular displacement of the binary image and a single iteration of the algorithm.

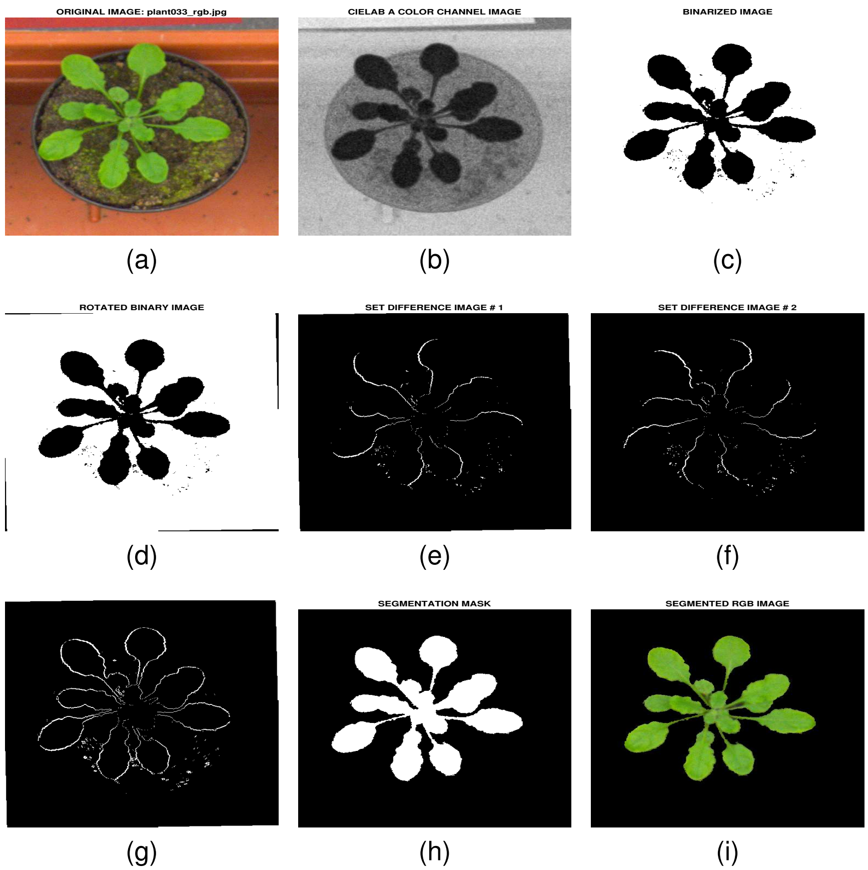

Fig. 4. (a) A rosette plant with ID plant033_rgb.jpg in the A1 dataset. (b) The rosette plant in (a) is transformed to a color channel in the CIELAB color space (c) Binary image of the image in (b). (d) 1 degree angular displacement image of (c). (e) Image derived from the set difference between the stationary binary image in (c) and the displaced binary image in (d). (f) Image derived from the set difference between the displaced binary image in (d) and the stationary binary image in (c). (g) Image derived from the symmetric difference between the images in (e) and (f). (h) Segmentation mask built from the symmetric difference image after a single iteration. (i) The segmented rosette plant.

Corresponding parameters for the segmented image in Fig. 3i are 3 degree angular displacement and 3 iterations.

The steps to extract plant leaves region in images with ID plant033_rgb.jpg and plant092_rgb.jpg in the A1 dataset from [17] are illustrated in Fig. 4 and Fig. 5, respectively. The soil in the tray containing the plants contain moss. Image analysis becomes more challenging because the green color of the moss is similar to the color of the leaves. The algorithm parameters for both images are 1 degree angular displacement of the binary image and a single iteration of the algorithm. Our proposed method recorded a foreground background Dice (FBD) dice score of 0.9584 for the image in Fig. 4. Corresponding score for the image in Fig. 5 is 0.9439.

The FBD score recorded by the proposed method on each of the 128 test images in the A1 dataset are displayed in Fig. 6a. Histogram distribution of the FBD recorded by the proposed method for all images in the dataset is in Fig. 6b. The performance of two state-of-the-art methods proposed by [8] and [10] on the A1 dataset was reported in [21]. The reported performance indices is compared with the performance of our proposed in Table 1.

Histogram distribution in Fig. 6b shows that the FBD recorded by the proposed method lies between 0.65 and 1. For the entire dataset, our proposed method recorded mean FBD score of 0.921 and standard deviation FBD score 0f 0.051. The mean FBD score of 0.921 recorded by our proposed method is comparable to the FBD scores of 0.946 and 0.962 recorded by [10] and [8], respectively. The standard deviation FBD score measures the robustness of an algorithm to varying scene complexities and different quality attributes in the image. Based on the standard deviation FBD score, our proposed method can be considered as more robust than the two current state-of-the-art methods. Standard deviation FBD score of 0.05 recorded by our proposed method is superior to the corresponding scores of 1.6 and 1.9 recorded by the other two methods.

The proposed method combines the discriminatory power of perceptual color space with the simplicity of threshold method. Our proposed method, unlike [10], was evaluated without additional resources such as image enhancement algorithm. The two current state-of-the-art methods extract the leaf region in relatively high dimensional perceptual color space. In our proposed method, the process of extracting the leaf region is executed in the binary domain. Processing in the binary

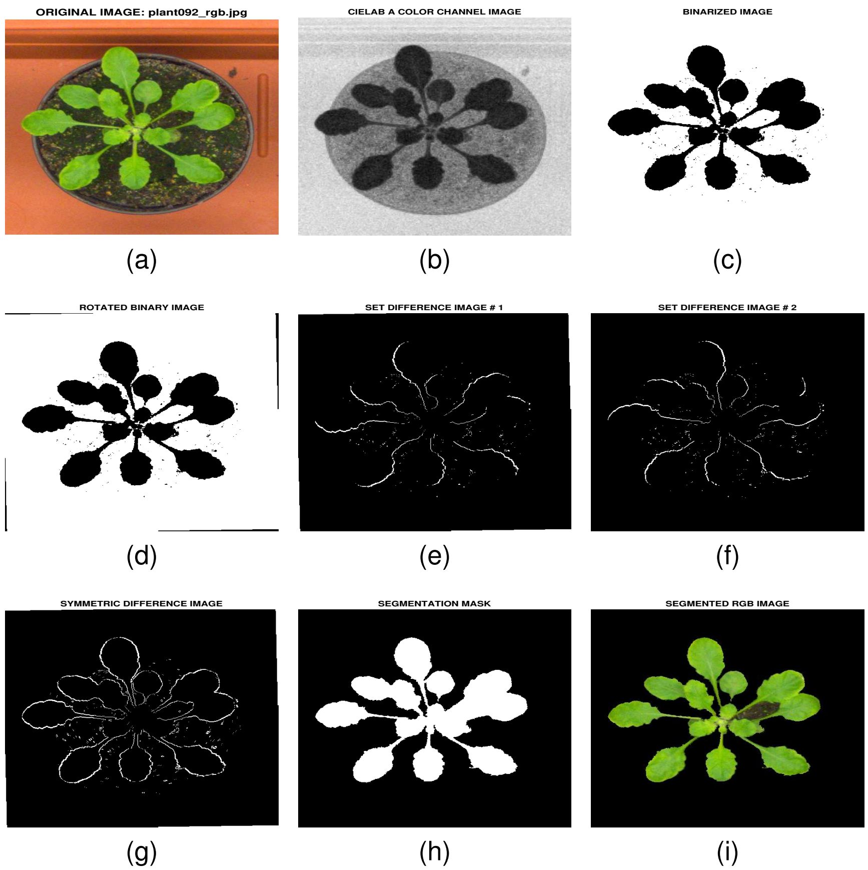

Fig. 5. (a) A rosette plant with identification number plant092_rgb.jpg in the A1 dataset. (b). The rosette plant in (a) is transformed to a color channel in the CIELAB color space (c) Binary image of the image in (b). (d) 1 degree angular displacement image of (c). (e) Image derived from the set difference between the stationary binary image in (c) and the displaced binary image in (d). (f) Image derived from the set difference between the displaced binary image in (d) and the stationary binary image in (c). (g) Image derived from the symmetric difference between the images in (e) and (f). (h) Segmentation mask built from the symmetric difference image after a single iteration. (i) The segmented rosette plant.

domain are naturally computationally efficient. This design feature makes our proposed method more computationally efficient than the two current methods.

TABLE I
COMPARATIVE PERFORMANCE EVALUATION OF LEAVES REGION EXTRACTION RESULTS FOR LEAF SEGMENTATION CHALLENGE A1 DATASET

METHODS	MEAN FBD	STANDARD DEVIATION FBD
Ref 8	**0.946**	**1.600**
Ref 10	**0.962**	**1.900**
PROPOSED	**0.921**	**0.051**

IV. CONCLUSION

Although plant leaves segmentation has been successfully addressed in many contributions, there is yet no known algorithm that has universal application to address all the challenges. Review of the literature show that there is need to develop simple and efficient algorithms. In this report, we propose an hybrid approach to extract leaves region in plant images. The proposed method combine the discriminatory power of perceptual color space with the simplicity of threshold-based method. The proposed method is computationally efficient and robust to different levels of scene complexities. Furthermore, its performance is comparable to selected state-of-the-art methods.

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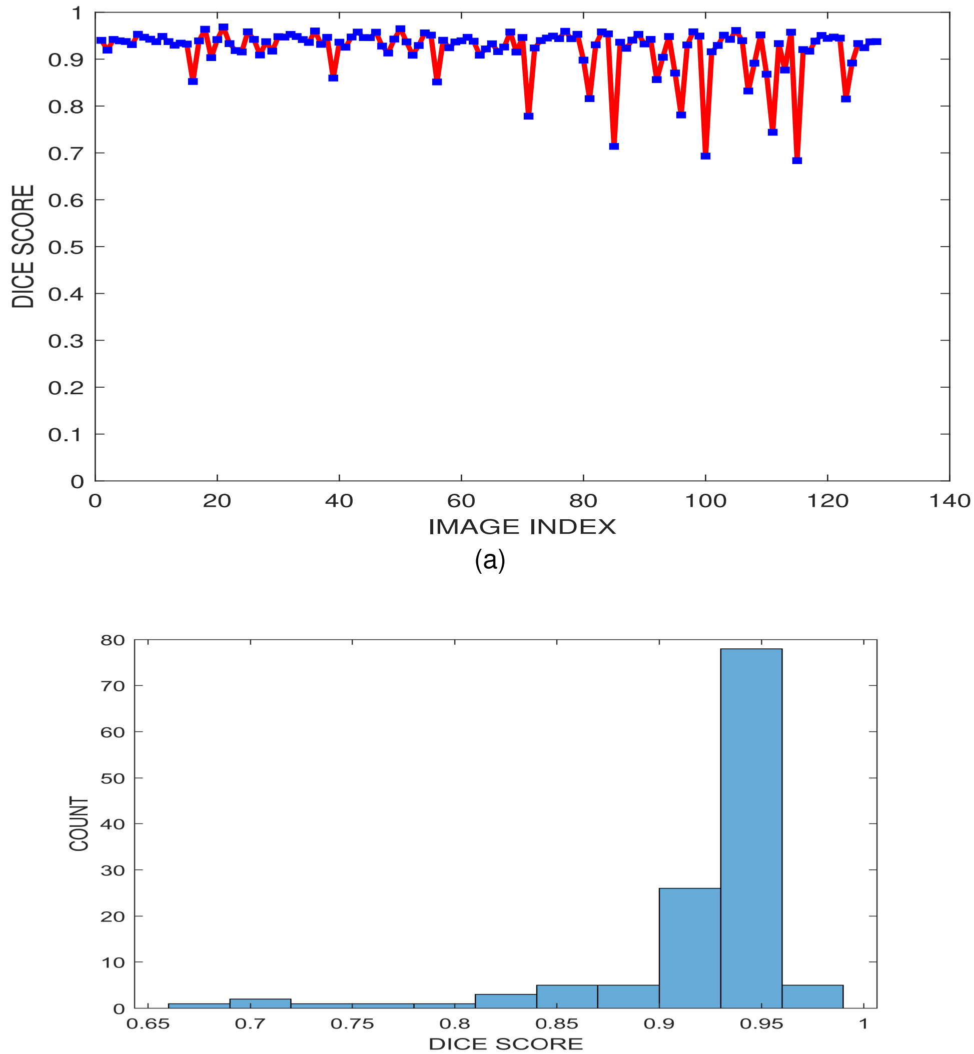

Fig. 6. Performance evaluation of the proposed method. (a) Plot of the foreground-background Dice score for each of the 128 test images. (b) Histogram distribution of the foreground-background Dice score for all the test images.

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