Segmentation of Lettuce Plants Using Super Pixels and Thresholding Methods in Smart Farm Hydroponics Setup

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Abstract— Segmentation is one of the significant requirements of efficient computer vision applied in plant growth monitoring. Existing segmentation techniques has their own merits, however should be selected for a specific situation with respect to varying plant environment. Consideration of segmentation in the context of lettuce in hydroponics environment remain an open research. In this paper, a lettuce plant segmentation by using thresholding and super pixels is proposed, which can classify lettuce plant and background from images taken at a smart farm hydroponics setup. Lab color information of the image extracted from a training image dataset undergo two-level thresholding and K-means clustering thru superpixels to identify each pixel class. Experimental testing results demonstrate an improved performance in segmentation in terms sensitivity, precision, and F1-score.

Index Terms— k-means clustering, lettuce segmentation, superpixels, simple linear iterative clustering algorithm, thresholding

I. INTRODUCTION

IMAGE segmentation is one of the most essential process in computer vision applied in plant growth monitoring [1]. The accuracy of identification of the plant growth depends on the efficiency of the isolation of plant to the background environment [2]. Several computer vision algorithms for plant growth monitoring were emphasized on the works about plant parts segmentation [3],[4], disease detection [5], feature extraction [6],[7] which remain challenging for plant imaging area.

Many supervised, unsupervised and semi-supervised methods from different perspectives have been proposed to address the image segmentation task [8]-[10]. However, each segmentation has its own merits and should be selected for a specific situation with respect to varying plant environment to address computer vision problems such as camera resolution, illumination changes [11], and scale invariance [12].

Although the vision-based lettuce growth monitoring has encountered several developments in recent years, some problems remain an open research area. Current studies have not satisfactorily resolved the challenges and requires improvement and extensive testing for functionality and robustness when applied in controlled greenhouse environment or smart farms. Manual segmentation was done in [13],[14] planted in open field. Most of the segmentation is scenario-dependent [15],[16], and limited studies have considered segmentation of lettuce in hydroponics setup.

Superpixels technique has experienced significant developments in its use in computer vision applications. Superpixels approach have been used in preprocessing [17], segmentation [18], and classification [19] with each approach has its own advantages. This study proposes a segmentation of lettuce plant which uses combination machine vision using K-means clustering thru super pixels and thresholding methods. Simple linear iterative clustering algorithm (SLIC) is used to create the superpixels.

This paper consists of five sections organized as follows. The first chapter presents some recent examples of segmentation. The second chapter discusses the background environment where the lettuce crops are planted and its inherent computer vision problems. Chapter 3 introduces K-means clustering and superpixels. Chapter 4 discusses the proposed methodology about plant segmentation using super pixels and thresholding. Experimental results and analysis are discussed on Chapter 5 followed by the last chapter for conclusions and future directions of the proposed work.

II. HYDROPONICS SETUP

The main objective of this study is to segment the region as lettuce plant and non-lettuce plant regions in a smart farm hydroponics setup. This kind of setup belongs to controlled-environment agriculture (CEA) [20] which is a horticultural technology supported by integrated science and engineering approach. In this setup such as shown in Figure 1, lettuce plants are planted hydroponically on rockwool that floats on top of holes on pipes. Nutrient solution flows through the pipes. This system enables better control of pests, conserves space and eliminates that need for constant watering.

The smart farm hydroponics chamber is designed to produce maximum number of harvestable crops. There is temperature control and an artificial light system installed. The vision system is developed to monitor the crop growth. The

nutrients solution is maintained according to recommended thresholds measured using pH and conductivity.

Fig. 1. Hydroponics setup for the proposed study

Lettuce images are captured on top view using a monocular camera. Artificial LED lighting is used as a source of white light and no direct sunlight is allowed inside the chamber to maintain the quality of the taken images. Some inherent problems encountered in image acquisition are intensity variations, illumination variations, blurred capture and background noises. Figure 2 shows some sample captured images.
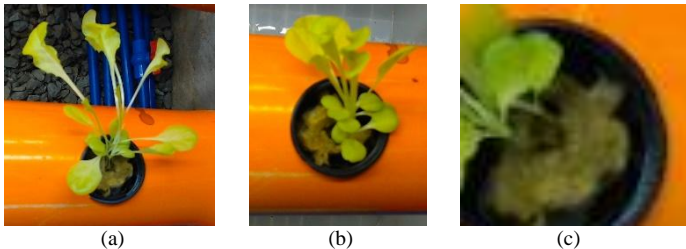

(a)   (b)   (c)

Fig. 2. Capture Setup for the proposed study (a) noisy background (b) blurred capture (c) greenish rock wool used for planting the lettuce similar in color with plant

III. K-Means & Super Pixels

A. K-Means

K-means is clustering method that group similar objects into k mutually isolated clusters. K-means clustering operates on assigning objects to the cluster that has the closest centroid on each iteration. The new centroids are then recalculated from the assigned data clusters. There are different distance measures, depending on the kind of data to be clustered. An example of Euclidean distance formula is shown in (1). The process of assigning data to centers and recalculation of new centers are repeated until convergence, such that no movement of data to another cluster is still happening [21]. K-means clustering have been used in many applications such as classification analysis [22], unsupervised machine learning [23], and machine vision [24].

$$E(r,c) = \sqrt{\sum_{i=1}^{n}(R_i - R_c)^2 + (G_i - G_c)^2 + (B_i - B_c)^2} \qquad (1)$$

Where E (r, c): The Euclidean distance of a pixel with spatial coordinates (r,c) using color components R_i,G_i,B_i (RGB) in reference to its centers R_c,G_c,B_c (RGB)

B. Super pixels

Superpixel has drawn popular use in computer vision applications. In the last few years superpixels are widely used in segmentation applications such as in [17-19]. There are several superpixels algorithms that in general has its own merit in improving computer vision applications [25]. SEEDS algorithm is used for applications for critical computing time required. Ncut algorithm are used to build a graph that generates superpixels that are more visually pleasing. SLIC algorithm are often used in pre-processing for segmentation however, in this study SLIC superpixels are used to improve segmentation technique based on thresholds.

The image is divided into multiple segments called superpixels. K-means classification algorithm classifies each pixel in the superpixel region to create image patches spatially coherent homogeneous structure that adheres well to image boundaries. Figure 3 shows an example of superpixel implementation. Superpixels carry more information as it aligns with intensity edges as compared to rectangular patch. Superpixels create consistent meaningful regions which can be utilized for succeeding image processing tasks and can be used to solve classification problems on superpixels regions instead over the full original image.
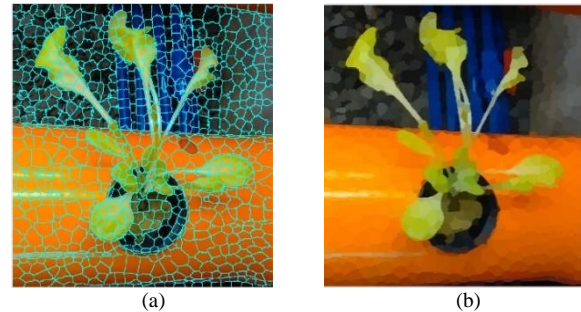

(a)   (b)

Fig. 3. Supexpixels implementation of Figure 2(a), (a) superpixel boundaries overlaid on the original image, (b) superpixel results

This research uses the concept of simple linear iterative clustering (SLIC). SLIC samples regularly spaced cluster centroids using k-means clustering applied spatially in every local superpixel regions. The algorithm has three basic steps. The cluster centroids are set first by considering pixels on regular grids. Next k-means clustering classifies every pixel local to a region to a single superpixel. Finally, the disconnected regions are reclassified with the class of the largest adjacent group for the connectivity of regions. SLIC computes the clustering distance by twofold, the color distance and spatial distance. The resulting superpixels of SLIC adhere well to the edge boundaries.

IV. PROPOSED METHODOLOGY

Figure 4 depicts the image processing techniques used in this research. The lettuce images taken on the smart farm hydroponics setup were processed to extract segmented lettuce plant. Segmentation were performed based on color features using K-means clustering and superpixels. Two-level thresholding fine-tuned the segmentation.

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┌──────────┐     ┌──────────┐     ┌──────────┐
│ Lettuce  │ →   │  Image   │ →   │ RGB to   │
│ images   │     │Enhancement│     │ CIELab   │
└──────────┘     └──────────┘     │conversion│
                                   └──────────┘
┌──────────┐     ┌──────────┐     ┌──────────┐
│ 1st level│     │Superpixel│     │Calculation of RGB│
│Thresholding│ → │computation│ → │ Mean for each │
│segmentation│    └──────────┘     │super-pixel region│
└──────────┘                       └──────────┘
┌──────────┐     ┌──────────┐     ┌──────────┐
│ K-Means  │     │ RGB to   │     │ 2nd level│
│Clustering by the│ → │ CIELab │ → │Thresholding│
│mean RGB color│   │conversion│    │segmentation│
└──────────┘     └──────────┘     └──────────┘
┌──────────┐     ┌──────────┐
│  Image   │ →   │Segmented │
│ Masking  │     │Lettuce pixels│
└──────────┘     └──────────┘
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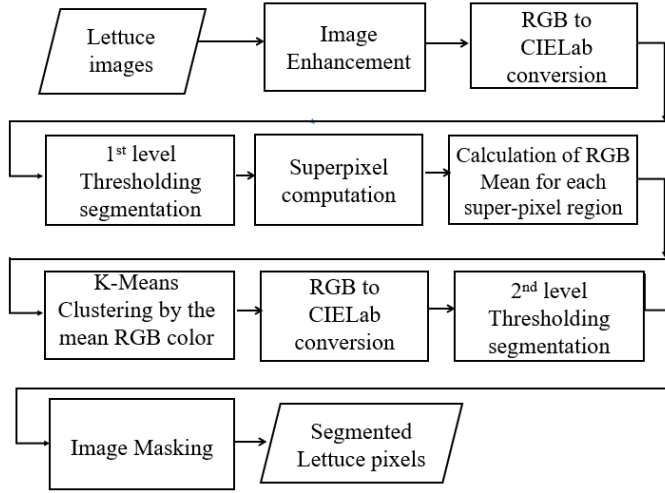
Fig. 4. Image processing techniques used in this research

The lettuce images in RGB color space were enhanced and converted to equivalent Lab color space. The Lab color space was derived from the XYZ tristimulus values. The Lab color space comprises of luminosity 'L', chromaticity 'a' and 'b'. 'L' corresponds to brightness layer while 'a' corresponds to chromaticity that is determined in the red-green axis, and 'b' corresponds to chromaticity that is determined in the blue-yellow axis. Transformation formulas to Lab from RGB is given in (2) to (7). X, Y and Z called the tristimulus values are RGB extrapolations.

$$X = 0.412456 * R + 0.357576 * G + 0.180437 * B \quad (2)$$
$$Y = 0.212673 * R + 0.715152 * G + 0.072175 * B \quad (3)$$
$$Z = 0,019334 * R + 0.119192 * G + 0.950304 * B \quad (4)$$
$$L = 116 f\left(\frac{Y}{100}\right) - 16 \quad (5)$$
$$a = 500 \left(f\left(\frac{X}{95.047}\right) - f\left(\frac{Y}{100}\right)\right) \quad (6)$$
$$b = 200 \left(f\left(\frac{Y}{100}\right) - f\left(\frac{Z}{108.883}\right)\right) \quad (7)$$

Next, images were segmented by labeling every pixel by the learned threshold of L, a and b for lettuce pixels and non-lettuce pixels. Each pixel was set that qualifies statement in (8) as lettuce pixels otherwise as non-lettuce pixels. If P was true then [L(i,j),a(i,j),b(i,j)] was classifies as a lettuce pixel else [L(i,j),a(i,j),b(i,j)] a non-lettuce pixel. Histograms in CIELab used in first level segmentation is shown in Figure 5. The output image here was still in an RGB image.

$$P= (a(i,j) < a_l) \; \&\& \; (a(i,j) > a_u) \; \&\& \; (L(i,j) > L_l) \&\& \; (Ls(i,j) < L_u) \; \&\& \quad (8)$$
$$(b(i,j) > b_l) \; \&\& \; (b(i,j) < b_u)$$

Where a (i, j), b(i,j),L(i,j) are CIELab color space components with spatial coordinates (i,j), a_l, L_l, b_l and a_u, L_u b_u are CIELab learned lower thresholds and upper thresholds respectively.

The superpixels of the resulting RGB image was then calculated. Simple linear iterative clustering (SLIC) algorithm was used in this research. Simple linear iterative clustering (SLIC) clustered five dimensional vectors. Thus, for each pixel 5 vectors were noted [R, G, B, x, y] color information and spatial position.
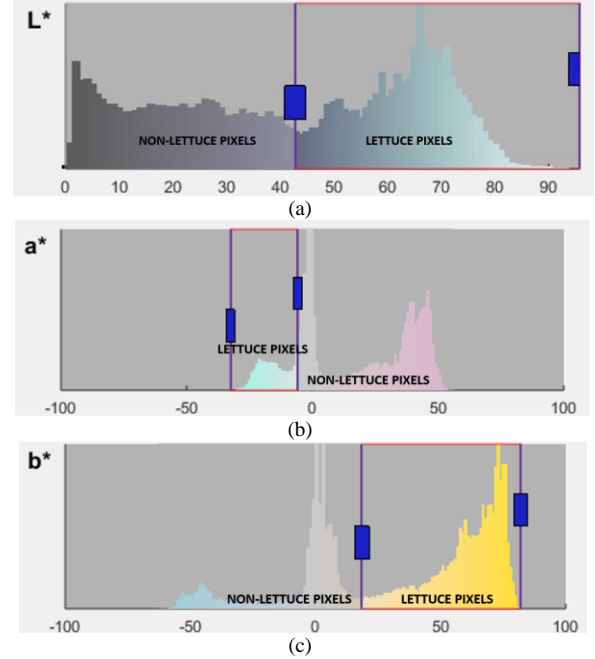

Fig. 5. Histograms in CIELab used in first level segmentation filtering out lettuce pixels, (a) Luminance, (b) chromaticity that is determined in the red-green axis (c) chromaticity that is determined in the blue-yellow axis

The detailed Superpixel algorithm used in this research can be described as follows:
1. Initialize the superpixels centers by sampling n locations on a regular grid in image plane. The number of superpixels considered here are 50, 500, and 1000. The compactness parameter is set to a constant value.
2. For each cluster center m_i with color information as (R_i,G_i,B_i) and spatial coordinates as (x_i,y_i), compute distance between m_i and each pixel with color information (R_j,G_j,B_j) located at (x_j,y_j) in a neighborhood of m_i using (9) to (11). Assign pixel to cluster i if its distance is better than its current value.

$$dc = \left\| \begin{bmatrix} Ri \\ Gi \\ Bi \end{bmatrix} - \begin{bmatrix} Rj \\ Gj \\ Bj \end{bmatrix} \right\|^2 \quad (9)$$

$$ds = \left\| \begin{bmatrix} xi \\ yi \end{bmatrix} - \begin{bmatrix} xj \\ yj \end{bmatrix} \right\|^2 \quad (10)$$

$$D = \sqrt{\left(\frac{ds}{S}\right)^2 + \left(\frac{dc}{C}\right)^2} \quad (11)$$

Where D is the total distance function, dc is color distance

function, ds is spatial distance function, C is maximum color distance, S is maximum spatial distance

3. Update the cluster centers using K-means
4. Repeat until convergence
5. Replace colors of pixels in each cluster with the average RGB color

The resulting superpixel RGB image was converted again to Lab color space. The 2nd level thresholding using the learned L, a and b thresholds were used to label every pixel as lettuce or non-lettuce pixels. Similar equation in Equation (8) but with updated threshold was used for segmentation. This process was used to isolate lettuce regions and create the binary mask.

To test the performance of the system in terms of segmentation, vision metrics and computational efficiency were evaluated in terms of sensitivity, precision, F1 score and computing time. Equations (12) to (14) are statistical evaluation criteria of the performance of the image segmentation. In the context of lettuce plant segmentation, sensitivity is the fraction of correct results which are positive (lettuce pixels). On the other hand, precision is the positive predictive value or the fraction of positive lettuce pixel classification results which are correct. The F1 score or simply F score is the harmonic mean of precision and recall (sensitivity). To determine these evaluations, ground truth (GT) images were identified by inspection and manually drawing the border around the lettuce plants and counting the number of correct lettuce pixels thru a program.

$$precision = \frac{TP}{TP + FP} \tag{12}$$

$$sensitivity = \frac{TP}{TP + FN} \tag{13}$$

$$F_1 score = 2 \times \frac{precision \ \times sensitivity}{precision + sensitivity} \tag{14}$$

V. DISCUSSION OF RESULTS

This section presents the results of the proposed segmentation method for lettuce. The methodology was evaluated on a set of 20 images of lettuce images obtained from Smart farm hydroponics setup. The ground truth images were found via human-based segmentation and counting thru a program the number of lettuce and non-lettuce pixels.

Figure 6 shows sample results of segmentation obtained using the proposed algorithm. Original lettuce image is shown in Figure 6(a). The RGB color image was then converted to its corresponding CIELab color space. Figure 6(b) to 6(d) shows the CIELab components of lettuce superpixels which were used to compare to learned thresholds shown in Figure 6(a) to6(c). Lettuce plant pixels were classified accordingly to their corresponding thresholds which is shown in Figure 6(e). It can be noticed at the leftmost leaf, the presence of some lettuce pixels converted to black pixels due to illumination. Boundaries for the regions was computed using 500 superpixels shown in Figure 6(f). Result of segmentation using SLIC is shown in Figure 6(g). It is worth noting in this

clustering, the edge information of the original images was carefully preserved. With this, the leaf color information which was too dark and too light were clustered effectively to their corresponding superpixel region bounded by the edges of the leaves. Finally, region of interest of segmented lettuce can be seen in Figure 6(h). Superpixels made a compact representation of the regions of the images. Superpixels grouped the lettuce pixels and non-lettuce pixels together making it very useful in further segmentation.

This study used 50, 500 and 1000 number of superpixels to test the performance of the system. Table 1 gives the performance of the system in terms of segmentation.
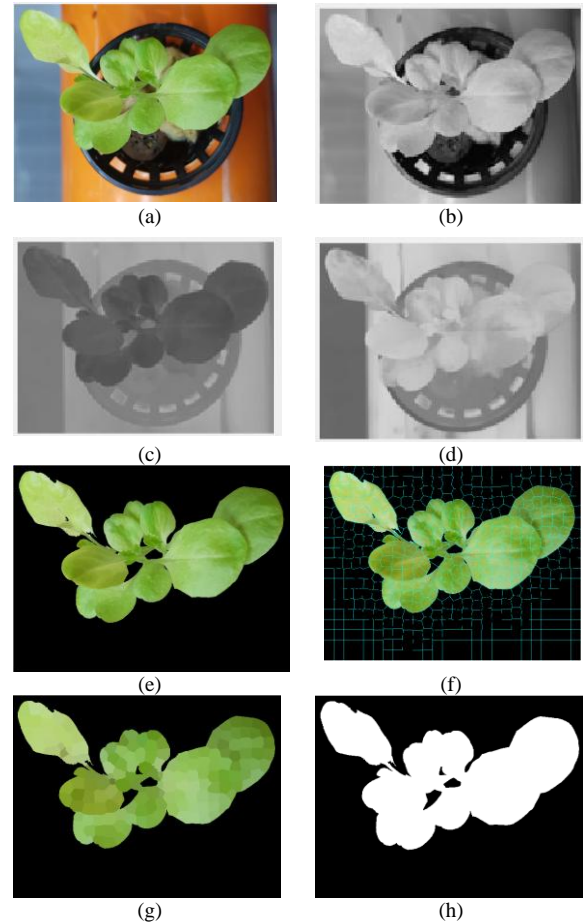

Fig. 6. Proposed segmentation process, (a) original image, (b) L component of CIELab conversion (c) a component of CIELab conversion (d) b component of CIELab conversion (e) 1st level thresholding based on CIELab (f) superpixel boundaries overlaid on the original image (g) Each superpixel regions were replaced by the regions' mean RGB (h) binary masking based on the 2nd level CIELab thresholding

TABLE I.
PERFORMANCE EVALUATION OF THE SYSTEM USING DIFFERENT NUMBER OF SUPERPIXELS REGIONS

No. of Superpixels	Sensitivity	Precision	F1-Score	Computing Time
n=0	0.992447	0.980764	0.986522	3.965996
n=50	0.982170	0.994207	0.987909	8.936581
n=500	0.997534	0.984113	0.990726	8.97144
n=1000	0.996141	0.988288	0.99214	9.017033

Notable improvements of segmentation for the proposed methods in terms of sensitivity, precision and F1-score are apparent in Table 1 compared to n=0 (Thresholding only). Selecting a more appropriate number of superpixels regions for the study presented here can improve the performance of the segmentation application. From the results, it was found out that n=500 performs best considering sensitivity while n=1000 performs best considering precision. However, an additional computing time of about 5 seconds is required.

Since F_1 score is the harmonic mean of precision and sensitivity, it achieves its best value when precision and recall are both high and of similar value. An optimal setting for sensitivity and precision can be achieved if the best F_1 score is required as illustrated in Figure 7. Based on the results (n=0,50,500 and 1000), the proposed methodology with the 1000 number of superpixel regions obtained the highest F_1 score.
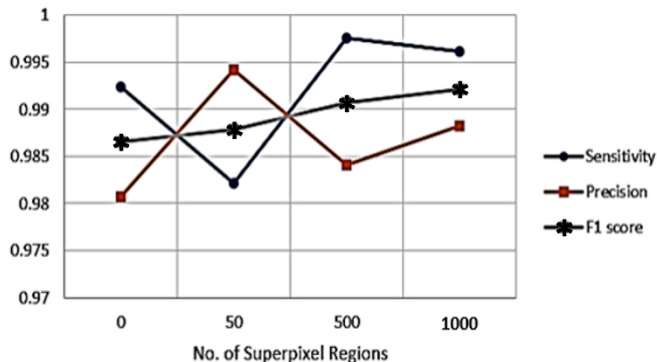

Fig. 7. Sensitivity, Precision and F_1-score vs. number of superpixel regions

VI. CONCLUSIONS

A proposed method using SLIC superpixels, two-level CIELab thresholding is proposed for segmentation of lettuce plant in a smart farm hydroponics setup. Based on the results, the methodology has improved segmentation of lettuce plant pixels and background pixels. Testing gave a high performance in segmentation in terms sensitivity, precision and F1-score for an additional computing time of about 5 seconds. F1-score identified experimentally, n=1000 supepixel regions as the optimal value for best performance in terms of sensitivity and precision. Future work includes modification of the methods to further segment leaves and stem from the segmented lettuce plant.

ACKNOWLEDGMENT

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