P-ISSN 2586-9000
E-ISSN 2586-9027
Homepage : https://tci-thaijo.org/index.php/SciTechAsia
Science & Technology Asia
Vol.27 No.2 April - June 2022
Page: [171-178]
Original research article

A Segmentation Algorithm for the Leaf Area Identification in Plant's Images

Abhishek Gupta*

School of Computer Science and Engineering, Shri Mata Vaishno Devi University, Katra, Jammu and Kashmir 182320, India

Received 28 June 2020; Received in revised form 23 March 2021
Accepted 21 April 2021; Available online 29 June 2022

ABSTRACT

The agricultural field is emerging for solving problems using computer vision algorithms. To monitor the plants based on leaf segmentation is also one of the essential requirements in the near future where there will be no manual work for the cultivation and growth of the plants. In this paper, an algorithm is proposed for the automatic monitoring of the plant based on leaf segmentation. The proposed algorithm does not take much time and also is recommended to use in real-time monitoring. The algorithm was validated on two databases and results were found satisfactory to use it for monitoring purposes. A method of plant monitoring based on leaf segmentation is also discussed for the future enhancement of this work. The combination of the proposed algorithm and method of monitoring will aid in designing a fully automated system for the monitoring of plants.

Keywords: Automatic monitoring; Image processing; Phenotype; Plant leaf monitoring; Segmentation

1. Introduction

Image processing techniques are playing an important role in agricultural applications. Significant research is currently going on not only in the agricultural field [1-4] but also in other fields based on image processing and computer vision approaches. Agricultural problems are solved using several approaches of image processing to introduce automation in the field.

Automation is very useful and essential in the agricultural sector. The quality of production could be increased with the aid of computers. Conventionally, all the mundane activities in the agricultural sector are executed by humans; this has a higher cost and limited observations. With the introduction of computer automation, the same activities can be executed easily with less human intervention. To increase the production and to reduce the cost of the agricultural product, automatic surveillance is required. It is very difficult for people to manage or monitor large fields, whereas a camera can do it 24x7 and with good efficiency.

***Corresponding author:** abhishekgupta10@yahoo.co.in

Hence, computer-based monitoring is very useful in the agricultural field.

A surveillance camera is not enough for the monitoring of a large field. Again, it requires an operator for the observations which would increase the cost of the process. Also, it would not be feasible for a human. Hence, the automatic system is required which may detect the growth as well as the phenotype of the plant and an instruction would be generated for the necessary pruning or follow-up. This process may also record the different stages of plant growth, which may be referred to the assessment of growth of another plant [5].

Several researchers are working in these areas for leaf segmentation, disease detection on leaves and phenotype detection. Table 1 shows the related studies in the field of plant leaf segmentation. A few researchers have designed the database for the leaf segmentation challenge [6-7]. Along with the database images, ground truths were also published for the public use. Researchers have also designed a high throughput framework that could be able to find the length of leaf and area at a large scale. While the current study is not fulfilling the scaling factor, it could be implemented in future.

Table 1. Related work in the field of plant's leaf segmentation.

Reference with year	Objective	Sample Size	Work done	Results	Remarks
Yin et al. (2017) [8]	Multi-Leaf Segmentation, Alignment, and Tracking for Fluorescence Plant Videos	389 frames from each of 41 Arabidopsis Thaliana videos	A framework was designed for segmentation and tracking of fluorescence plants	Performance is evaluated based on qualitative evaluation scheme	Proposed algorithm was compared with state of the art methods and solved the problem of leaf segmentation, alignment and tracking
Ozturk et al. (2017) [9]	leaf segmentation with different illumination condition	26	Hybrid neural network model was used for the segmentation	Accuracy is obtained 99% on the uniform simple background	Experiment was performed on the 4 different types of leaves in different illumination conditions with simple background and there was only 1 leaf in 1 image.
Viaud et al. (2017) [10]	Automatic Leaf segmentation and leaf tracking	21*4=84 images	Leaf segmentation and tracking for genotype differentiation	Segmentation was conducted using phenoscope software	4 genotypes of Arabidopsis thaliana were used for the study. Angle for each leaf was analysed. There was no background existing in leaf images.
Barbedo et al. (2016) [11]	Semi-automatic segmentation of plant leaf disease symptoms	938	Semi-automatic algorithm was proposed for signs and symptoms of plant disease	Disease lesions were segmented in 83% cases	The algorithm is useful for the assessment of plant disease based on the leaves with a large number of varieties.
An et al. (2016) [12]	A high-throughput framework was designed to measure leaf length and rosette area	Real time plant image acquisition system was used	Real time cluster computing was used for reducing the processing time of segmentation of leaf and tracing	An efficient scalable system was designed for the analysis of plant's leaf	A system was developed for producing results with high-throughput

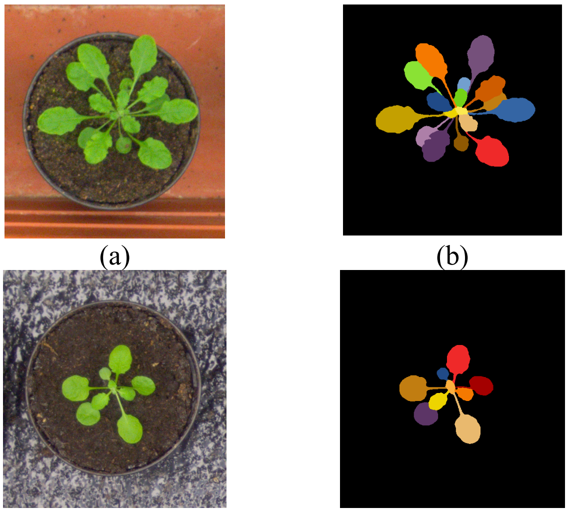
Researchers have conducted the experimental studies for the segmentation of leaf [9, 13], recognition of leaf [14], monitoring and tracking of plants [8] based on leaf in visible as well as in infrared spectrum [15]. A few studies were also conducted at a large scale to fulfil the problem of scalability [12]. Along with these studies, work is also ongoing in the direction of automatic detection of plant leaf diseases [3, 11, 16]. These types of problems have the similar challenge to segment the plant's leaf with higher accuracy. Once the segmentation of the leaf is established as mentioned other relevant challenges would be solved. By comparing the relevant studies in the field [17], a novel approach is proposed in this paper for the segmentation of a plant's leaf for the automatic monitoring.

2. Materials and Methods

2.1 Materials

For the purpose of the validation of the proposed algorithm, Arabidopsis thaliana plant image datasets A1 and A2 were used [6-7]. The datasets A1 and A2 have images with different resolutions, 500X530 pixels and 530X565 pixels, respectively. The number of images used in A1 dataset was 128 and in A2 dataset 31. Thus, a total of 159 images were used in the study for the validation of the proposed algorithm.

Both the datasets were acquired in different backgrounds and different environmental conditions. The backgrounds of these datasets are not so simple and the pots of the plant are also different. In each dataset, the background is changing along with an illumination effect of shadow. The image datasets already have the noises and artefacts. The images acquired in these datasets are taken at different stages of growth. The ground truth for the leaf segmentation of each image was received from the same source, also shown in Fig. 1.



(a) (b) (c) (d)

Fig. 1. Arabidopsis thaliana plant image datasets; images (a) and (c) belong to A1 and A2 datasets and image (b) and (d) are the segmentation ground truth of the image (a) and (c), respectively.

2.2 Methods

2.2.1 Proposed segmentation method

An algorithm has been proposed and developed in this paper for automatic segmentation of a plant's leaf. A proof of concept of this algorithm is developed in the MATLAB programming environment. The flowchart of the algorithm is shown in Fig. 2.

The algorithm takes a plant's RGB image as an input and a green color frame is extracted from the image. For the preprocessing of the image, an averaging filter is adopted for the removal of the noise. After noise removal, edges are detected using the Sobel edge detection algorithm. On the 2nd copy of the filtered image, color thresholding is applied to the extraction of the green color. Based on the output image from both the channels, a combined image is obtained containing edges and a thresholded green area of the image, which is a possibly leaf area.

A few morphological operations were performed to avoid the dis-connectivity of the segmented part of the leaves. The image was dilated using the morphological operations. It is assumed that one image is only 1 plant. Therefore, it is assumed that it may be found at the centred location of the image. To remove other noise components due to the edge filter, other components were dropped except the centred component which is the segmented leaf area of the plant. To avoid the extrapolated amount of leaf area, morphological operations were performed again. An image erode function was performed with the same mask to get the original image. With these operations, we get the segmented leaf area. The complete algorithm is also demonstrated using a flow chart in Fig. 2. A sample intermediary image is also shown along with the corresponding step to have a flavor of understanding of intermediary steps.

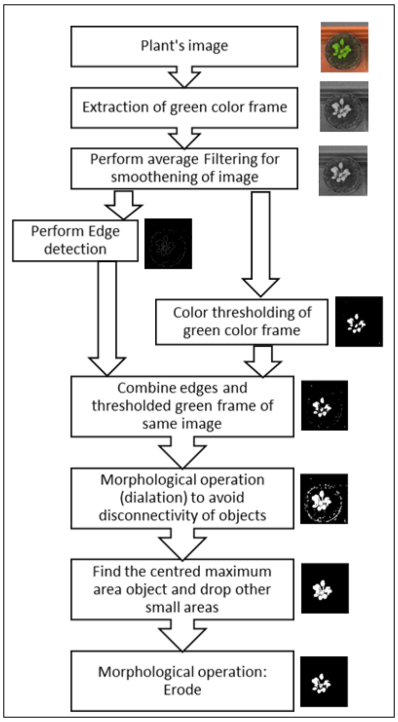


Fig. 2. Flowchart of the proposed algorithm along with the intermediary images of each step during processing of plant's leaf segmentation.

2.2.2 Method of validation

The proposed algorithm was implemented in the MATLAB programming environment and evaluated on two datasets, as mentioned in the materials and methods section. The ground truth of each image was also received along with the dataset, and a sample is shown in Fig. 1. The outcome of the proposed algorithm was compared with the given ground truth and the following performance parameters were computed for the assessment of the proposed method.

1. Accuracy: it is defined as the ratio of addition of true positive (TP) and true negative (TN), and addition of TP, TN, false positive (FP) and false negative (FN). This factor gives the segmentation accuracy of the proposed algorithm compared to the given ground truths as shown in Eq. (2.1).

$$\text{Accuracy} = (TP+TN) / (TP+TN+FP+FN) \tag{2.1}$$

2. Specificity: it is defined as the ratio of TN and addition of TN and FP values. It provides the proportion of actual negatives which were correctly segmented as shown in Eq. (2.2).

$$\text{Specificity} = TN / (TN+FP) \tag{2.2}$$

3. Sensitivity: it is defined as the ratio of TP and addition of TP and FN values. It provides the proportion of actual positives which were correctly segmented as shown in Eq. (2.3).

$$\text{Sensitivity} = TP / (TP+FN) \tag{2.3}$$

4. F-Score: it is a harmonic mean of precision and recall. It measures the test's accuracy by considering precision and recall of the test as shown in Eq. (2.4).

$$\text{F-Score} = 2*TP / (2*TP+FP+FN) \tag{2.4}$$

The above mentioned performance parameters were computed based on the values of TP, TN, FP, and FN and these were obtained as the number of pixels when compared to the results of the proposed algorithm with the ground truth at pixel level.

This comparison was performed based on the bit-wise operations of pixels between the proposed algorithm's result and ground truth.

2.2.3 Monitoring of plant

Images acquired through the database were taken within an interval of time. This interval can be represented by a certain time. There is a growth in the plant leaf area during each acquisition of images. This growth can be recorded in terms of segmented leaf area and number of leaves as well. If there is a significant difference in the sequential images of a plant's leaves in the area and number of leaves, ignoring the segmentation accuracy, then it can be termed as the growth of the plant in the particular gap of image acquisition of the same plant. Images in Table 2 and Table 3 indicate the different area of leaves in the same database visually.

Table 2. The results of Plant's leaf segmentation on dataset 'A1' using proposed algorithm.

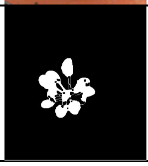
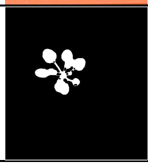
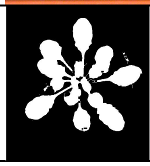
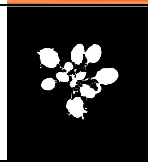
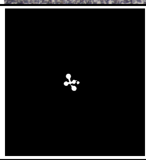
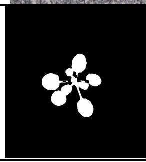
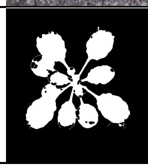
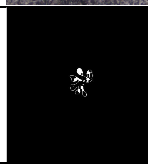
Sample images	**Image 1**	**Image 2**	***Image 3***	***Image 4***
Input Image				
Result from proposed algorithm				
Accuracy	0.9877	0.9961	*0.9701*	*0.9690*
Specificity	0.9965	0.9976	*0.9937*	*0.9968*
Sensitivity	0.8625	0.9623	*0.7942*	*0.8330*
F-Score	0.9017	0.9534	*0.9629*	*0.8614*

Table 3. The results of Plant's leaf segmentation on dataset 'A2' using proposed algorithm.

Sample images	***Image 5***	***Image 6***	***Image 7***	***Image 8***
Input Image				
Result from proposed algorithm				
Accuracy	*0.9839*	*0.9965*	*0.9796*	*0.9897*
Specificity	*0.9997*	*0.9979*	*0.9940*	*0.9988*
Sensitivity	*0.8752*	*0.9747*	*0.9219*	*0.3379*
F-Score	*0.9095*	*0.9715*	*0.9499*	*0.4752*

To monitor the plant's growth, the algorithm's segmentation accuracy should be evaluated and established. The amount of true positive is considered as the area of the segmented plant's leaf. The difference of true positives in the sequential images is computed as the growth of plants.

3. Results and Discussion

A few sample images from both the datasets are shown in Table 2 and Table 3 along with the performance parameters. Fig. 3 shows the graph of the same performance parameters for all the images in database A1. Table 4 shows the average value of each performance parameter calculated for each image in each database. Accuracy, specificity, sensitivity and F-Score were obtained as 0.9631, 0.9889, 0.8213, and 0.8608, respectively, for database A1. Similarly, accuracy, specificity, sensitivity and F-Score were obtained as 0.9677, 0.9980, 0.7141, and 0.7668, respectively, for database A2.

Table 4. The average segmentation results of each database based on the mentioned parameters.

Dataset	Accuracy	Specificity	Sensitivity	F-Score
A1	0.9631	0.9889	0.8213	0.8608
A2	0.9677	0.9980	0.7141	0.7668

The average value indicates the excellent accuracy of the segmentation using the proposed algorithm. The performance parameter shows the satisfactory results of the proposed algorithm.

Fig. 3 indicates good accuracy and specificity for all the samples. Although sensitivity and F-Score are not good for all the samples, the reason may be that a very small area of the leaf in a few images are not sensed by the proposed algorithm.

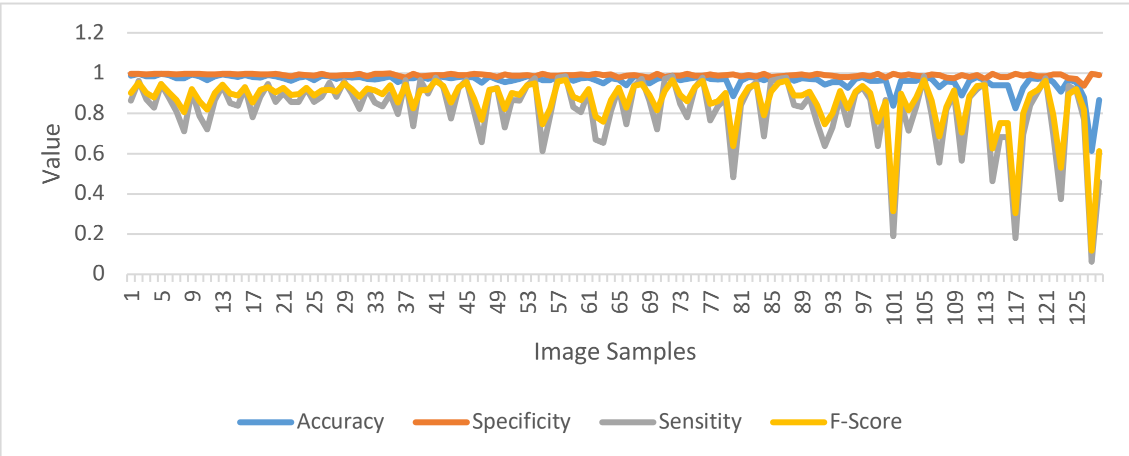


Fig. 3. Evaluation results of proposed algorithm on the plant's image dataset 'A1'. This dataset has 256 images. The result of each image is shown in the parameter of accuracy, specificity, sensitivity and F-score. The number of sample images is shown on the x-axis and values of each image corresponding to mention 4 parameters are shown on the y-axis.

The proposed algorithm is not based on any training. It is a color and edge-based algorithm which is applicable for the images having only one plant in one image. Multiple plants in one image are not applicable to the proposed system. However, multiple plants could be segmented plant-wise using the grid structure, then the proposed algorithm can be useful for such images.

The proposed algorithm is applicable to real time processing as the performed operations do not require much computation time. A camera can be mounted over the plant for 24X7 monitoring of plant to reduce the manual work.

The differences of true positive values of each image in sequential acquisition are calculated for the computation of growth which is in an early phase. The results of such computation are the future work of this paper. Based on the results, growth prediction will also be conducted by establishing a relation between the experimental data of growth. This will help to design a system that will automatically monitor the plants and predict the growth of the plant which is our future work relevant to this paper.

This work was completed using visible camera. However, a few researchers are pursuing similar work using the infrared camera which provides a different opinion and may helpful significantly in the current field. Therefore, the use of infrared cameras in the similar types of study [15, 18] is also a future enhancement of the work. Additionally, the combined view of visible and infrared camera has also given new dimensions of the significant research in the current field.

4. Conclusion

An algorithm is proposed for the automatic segmentation of a plant's leaf. The result of proposed algorithm is satisfactory for the application. The method of assessment of the segmentation results is also listed and implemented for the same algorithm. Additionally, a computational method for the automatic monitoring of the plant is also proposed for the future work.

Acknowledgements

The author would like to acknowledge the work completed under the project grant RP-103 received from the UGC.

References

[1] Vibhute A, Bodhe SK. Application of image processing in agriculture: A survey. International Journal of Computer Application. 2012;52(2):34-40.

[2] Wäldchen J, Rzanny M, Seeland M, Mäder P. Automated plant species identification—Trends and future directions. PLOS Computational Biology. 2018;14(4):e1005993.

[3] Raza S-e-A, Prince G, Clarkson JP, Rajpoot NM. Automatic Detection of Diseased Tomato Plants Using Thermal and Stereo Visible Light Images. PLoS ONE. 2015;10(4):e0123262.

[4] Neeraj Kumar PNB, Arijit Biswas, David W. Jacobs, W. John Kress, Ida Lopez, and JoÃco V. B. Soares. Leafsnap: A Computer Vision System for Automatic Plant Species Identification. In The 12th European Conference on Computer Vision (ECCV)2012.

[5] Sharma S, Gupta A. A review for the automatic methods of plant's leaf image segmentation. International Journal of Intelligence and Sustainable Computing. 2020;1(1):101-14.

[6] Minervini M, Abdelsamea MM, Tsaftaris SA. Image-based plant phenotyping with incremental learning and active contours. Ecological Informatics. 2014;23:35-48.

[7] Hanno Scharr MM, Andreas Fischbach, Sotirios A. Tsaftaris. Annotated Image Datasets of Rosette Plants. Technical Report No FZJ-2014-03837, Forschungszentrum Jülich.2014.

[8] Yin X, Liu X, Chen J, Kramer DM. Joint Multi-Leaf Segmentation, Alignment, and Tracking for Fluorescence Plant Videos. IEEE transactions on pattern analysis and machine intelligence. 2018;40(6):1411-23.

[9] Ozturk S, Akdemir B, editors. Automatic leaf segmentation using grey wolf optimizer based neural network. 2017 Electronics; 2017 19-21 June 2017.

[10] Viaud G, Loudet O, Cournède P-H. Leaf Segmentation and Tracking in Arabidopsis thaliana Combined to an Organ-Scale Plant Model for Genotypic Differentiation. Frontiers in Plant Science. 2016;7:2057.

[11] Barbedo JGA. A novel algorithm for semi-automatic segmentation of plant leaf disease symptoms using digital image processing. Tropical Plant Pathology. 2016;41(4):210-24.

[12] An N, Palmer CM, Baker RL, Markelz RJC, Ta J, Covington MF, et al. Plant high-throughput phenotyping using photogrammetry and imaging techniques to measure leaf length and rosette area. Computers and Electronics in Agriculture. 2016;127:376-94.

[13] Gupta A, Prakash D. A fast and efficient color model for automatic monitoring of plants based on leaf images. Journal of Critical Reviews. 2020;7(17):2398-404.

[14] Wu SG, Bao FS, Xu EY, Wang Y, Chang Y, Xiang Q, editors. A Leaf Recognition Algorithm for Plant Classification Using Probabilistic Neural Network. 2007 IEEE International Symposium on Signal Processing and Information Technology; 2007 15-18 Dec. 2007.

[15] Aksoy EE, Abramov A, Wörgötter F, Sharr H, Fischbach A, Dellen B. Modeling leaf growth of rosette plants using infrared stereo image sequences. Computers and Electronics in Agriculture. 2015;110:78-90.

[16] Zhang S, Wang H, Huang W, You Z. Plant diseased leaf segmentation and recognition by fusion of superpixel, K-means and PHOG. Optik. 2018;157:866-72.

[17] Scharr H, Minervini M, French AP, Klukas C, Kramer DM, Liu X, et al. Leaf segmentation in plant phenotyping: a collation study. Machine Vision and Applications. 2016;27(4):585-606.

[18] Chéné Y, Belin É, Chapeau-Blondeau F, Caffier V, Boureau T, Rousseau D. Anatomo-functional bimodality imaging for plant phenotyping: An insight through depth imaging coupled to thermal imaging 2013.