LAI Estimation of Cucumber Crop Based on Improved Fully Convolutional Network

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Abstract—LAI (Leaf Area Index) is of great importance for crop yield estimation in agronomy. It is directly related to plant growth status, net assimilation rate, plant photosynthesis, and carbon dioxide in the environment. How to measure LAI accurately and efficiently is the key to the crop yield estimation problem. Manual measurement consumes a lot of human resources and material resources. Remote sensing technology is not suitable for near-Earth LAI measurement. Besides, methods based on traditional digital image processing are greatly affected by environmental noise and image exposure. Nowadays, deep learning is widely used in many fields. The improved FCN (Fully Convolutional Network) is proposed in our study for LAI measure task. Eighty-two cucumber images collected from our greenhouse are labeled to fine-tuning the pre-trained model. The result shows that the improved FCN model performs well on our dataset. Our method's mean IoU can reach 0.908, which is 11% better than conventional methods and 4.7% better than the basic FCN model.

Index Terms—Leaf Area Index, FCN, Image Segmentation, Deep Learning

I. INTRODUCTION

Leaf area index (LAI) is a dimensionless quantity that characterizes plant canopies. It is defined as the one-sided green leaf area per unit ground surface area (LAI = leaf area / ground area, m² / m²) in broadleaf canopies [1]. It is related to vegetation density, structure, biological characteristics, and environmental conditions, a comprehensive indicator that reflects the canopy structure vegetation utilization of light energy. According to LAI’s definition, LAI’s value is larger with the increase of the degree of staggered and overlapping leaves. In the energy flow of the ecosystem, luminous energy is mainly absorbed and transformed by the plant. LAI, an important biological index that can characterize luminous energy absorption on a large scale. It can directly reflect the energy, CO₂ [2] and material cycles in the plant canopy of various scales. It is also directly related to many ecological processes, such as evapotranspiration, soil moisture balance, interception of canopy light, and net assimilation rate [3].

As a crucial biological structure parameter, LAI is challenging to obtain in a large area with manual measurement. Remote sensing technology provides conditions for this situation. Research work [4] combined remote sensing technology with a dynamic crop growth model to monitor parameters such as leaf area and canopy nitrogen status. Although remote sensing technology can obtain LAI in a large region, the value needs further ground verification. Therefore, it is essential to measure LAI at close range. Through digital hemispherical photography, research work [5] uses the deep learning method of the pix2pix model [6], which is to achieve vegetation image semantic segmentation for obtaining LAI. Digital hemisphere photography is suitable for data collection of forest vegetation.

However, for plants in the early stage of growth without forming a large canopy, capturing images from top to bottom is more suitable. The researchers often measure LAI with traditional digital image processing methods, such as a typical digital image segmentation Otsu [7] method. X. Li [8] proposed an improved Otsu algorithm to measure ginkgo LAI and achieved good segmentation results. M. H. Radzali [9] used Otsu to measure single leaf area. Besides, by mapping RGB to HSV [10] color space, it is right for leaf segmentation to extract the pixels in the image according to the green threshold. M. Li [11] borrowed this idea to do segmentation on wheat images.

There are some disadvantages of conventional image processing methods to measure LAI. On the one hand, if green distractors in the image, such as plant stems, roots, and weeds, these pixels will be included in the segmentation result, leading to a larger LAI. On the other hand, if the image is overexposed, these white pixels will not be included, leading to a smaller LAI. Methods based on threshold segmentation can not extract leaves intelligently. In this paper, our proposed method can solve the mentioned problems and demonstrate good performance. Furthermore, this method can show good performance on a small data set.

The paper is organized as follows. In section II, our method on measuring LAI is proposed. Section III provides our experimental setup and result analysis followed by the conclusion and discussion section IV.
II. PROPOSED SEGMENTATION METHOD

A. Network Architecture

There are many deep learning models in semantic segmentation, and the pioneering work of semantic segmentation, which bases deep learning, is FCN [12]. The author of FCN used VGG16 [13] as a convolutional part to extract image features. The result shows that FCN-VGG16 performs better than FCN-AlexNet [14] and FCN-GoogLeNet [15]. Also, the author pointed out that 8x upsampling performs better than 16x and 32x upsampling. Based on this idea, VGG16 is kept as a convolutional part. 2x upsampling rather than 8x upsampling improves this paper’s performance. Figure 1 shows our improved FCN architecture, which is called FCN-2s like FCN-8s in the paper [12].

B. Loss Function

The input of FCN-2s is an RGB image, and the network outputs a binary image as a segmentation result. Therefore, Binary Cross-Entropy Loss is used in our network for iteration and training. The loss function is as follows

$$L = -\frac{1}{N} \sum_{i,j} (y_{i,j} \times \log \hat{y}_{i,j} + (1 - y_{i,j}) \times \log(1 - \hat{y}_{i,j}))$$

(1)

Where, $N$ represents the total number of pixels in the binary output image (or label of the input), $y_{i,j}$ is the value of the $i^{th}$ row and $j^{th}$ column on the label. Similarly, $\hat{y}_{i,j}$ is the value of the $i^{th}$ row and $j^{th}$ column on the output of FCN-2s.

Before using the loss function above, the sigmoid function must act on the output. Therefore, the value will be between 0 and 1. In our task, since only the leaf part needs to extract, the label should be 0 or 1. 0 is defined as the leaf part and 1 as the background. From the formula above, it is evident that when $y_{i,j}$ is 1, then $1 - y_{i,j}$ is equal to 0. Therefore the closer $\hat{y}_{i,j}$ is to 1, and the minor loss will be. The conclusion reaches the same when $y_{i,j}$ is equal to 0. It is in line with our expectations: to make the output close to the label.

C. Improved unsampling structure

Usually, FCN is performed up to 8x upsampling. Details of the output of FCN are better from 32x to 16x up-sampling and from 16x up-sampling to 8x up-sampling. The experiment also shows that the segmentation result of contour boundary is improved with the sampling multiple decreases. Based on this idea, whether the sampling multiple can decrease to the minimum is considered. Therefore, a 2x upsampling method is adopted to improve the performance. Theoretically, the visual features extracted from convolutional layers in different depths can be used for upsampling, making the result better. It turns out to be accurate, and it will be proved in the next section.

Assuming that the upsampling factor is 2, it means that the convolution operation’s step size is 0.5. In the FCN-2s architecture, deconvolution is used for upsampling. Here, the deconvolution filter does not need fixed parameters. Because it can learn the optimal parameters through backpropagation, deconvolution layers can learn non-linear upsampling sometimes. It is appropriate to use deconvolution for upsampling.

D. LAI calculation formula

Once the semantic segmentation result from the network is obtained, LAI can be calculated. The total number of pixels $N_{soil}$ and the number of green leaf pixels $N_{leaf}$ are respectively counted. The ratio of the two variables above is the $LAI_{image}$ of the image. The calculation formula of LAI is as follows

$$LAI_{image} = \frac{N_{leaf}}{N_{soil}}$$

(2)
III. EXPERIMENT AND RESULT

The proposed model was implemented by using the Pytorch framework, as well as FCN-8s. OpenCV is a powerful library for computer vision, which is used to implement the two remaining methods. The network was trained using SGD with weight decay 0.0001, momentum 0.9, and a mini-batch of 4 on one Nvidia 2080 GPU. The learning rate was initially set to 0.00001. The whole experiment was running on a Windows system, and one Nvidia 2080 graphics card was for training during the experiment. Cucumber was selected as the planting object. A total of 82 cucumber pictures were obtained with two Hikvision cameras. The labelme [16] software was used to mark our cucumber dataset. Figure 2 shows the result of labeling one of the pictures by labelme. It can be seen from the figure that red points label all the leaf outlines. Then, the annotated images were generated by labelme. After that, the annotated images were converted into binary images to make the labels of our dataset.

The cucumber dataset was divided into the training set, validation set, and testing set according to the ratio of 8:1:1. On the cucumber dataset, the size of the original image is 1920x1080. Each image is compressed at 320x320 pixels to speed the training progress. All models for the cucumber dataset, including the FCN-8s and proposed model, were trained for 200 epochs with the same training configuration. For a fair comparison, the same testing set was used to evaluate all models.

The performance evaluation indicators given in the FCN model’s paper are used to evaluate the results of Otsu, HSV, FCN-8s, and ours. Let $n_{ij}$ be the number of pixels of class $i$ predicted to belong to class $j$, where there are $n_c$ different classes, and let $t_i = \sum_j n_{ij}$ be the total number of pixels of class $i$. The following metrics can be computed:

- pixel accuracy: $\frac{\sum_i n_{ii}}{\sum_i t_i}$
- mean accuracy: $(1/n_c) \sum_i n_{ii}/t_i$
- mean IoU: $(1/n_c) \sum_i n_{ii}/(t_i + \sum_j n_{ji} - n_{ii})$
- frequency weighted IoU: $\frac{(\sum_i t_i)^{-1}}{\sum_i t_i n_{ii}/(t_i + \sum_j n_{ji} - n_{ii})}$

Several pictures of the testing set were selected for displaying the contrast experiment results. The results of four segmentation methods are shown in Figure 3, Figure 4 and Figure 5 respectively.

Figure 3 (a) shows the cucumber’s top view in the non-seedling stage. It can be seen from the picture that, except for the leaves, there are no green objects. Therefore, it can be seen from the segmentation results of the four methods that the Otsu method has the worst performance. HSV seems to be very good in terms of blade edge details and contour performance, and FCN-2s is better than FCN-8s in edge details. The result of HSV is close to that of FCN-2s.

Figure 4 (b) shows the top view of the cucumber seedling stage. The difference from Figure 3 (a) is the germination stage of the cucumber image that there are not only green leaves but also green rhizomes in this picture. It is a challenge to the traditional threshold segmentation method. From the segmentation results of the four methods, the Otsu method...
has the worst effect. HSV not only extracts the leaves but also extracts the stems of the plants, with poor results. FCN-8s and FCN-2s seem to be the same. However, this picture has the characteristics of green distractors, and the leaves in the lower right corner of the original picture are overexposed and cause whiteness. It can be concluded that the HSV method cannot extract this exposed part at all from results. FCN-8s and FCN-2s have the same segmentation performance.

![Figure 5: Seedling stage of cucumber leaf segmentation results](https://example.com/f5.png)

Figure 5 (a) is the seedling stage of the cucumber picture. Similar to the semantic segmentation result in Figure 4, the HSV segmentation result is not very ideal due to plant stems in the picture. The results of Otsu are still poor. Compared with FCN-8s, FCN-2s is superior in image details and blade edge processing.

### TABLE I

| Method  | pixel acc. | mean acc. | mean IoU | f.w. IoU |
|---------|------------|-----------|----------|----------|
| Otsu    | 0.670      | 0.813     | 0.375    | 0.645    |
| HSV     | 0.985      | 0.961     | 0.820    | 0.979    |
| FCN-8s  | 0.990      | 0.919     | 0.867    | 0.984    |
| FCN-2s  | 0.992      | 0.948     | 0.908    | 0.988    |

Table I shows the four indicators of all the pictures on the testing set. Among the four indicators listed in Table I, the most important and capable of measuring the segmentation method’s quality is the mean IoU. The closer the value 1, the higher the overlap between the segmentation result and the label. From comparing the results of the four methods on the testing set, it can be concluded that Otsu has the worst performance under any indicator. Excepting the mean IoU indicator, HSV results under other indicators are comparable to the deep learning method. Even so, its mean IoU is much smaller than FCN-2s, the performance is still not ideal. From the comparison of FCN-8s and FCN-2s, FCN-2s is better than FCN-8s on all performance indicators, and the mean IoU of FCN-2s can reach 0.908. On the whole, the network proposed in this paper performs better than others on the cucumber dataset.

### IV. CONCLUSION AND DISCUSSION

For the LAI measurement, the FCN-2s model is applied to small cucumber data set in this paper. The result shows that FCN-2s performs better than FCN-8s, HSV, and Otsu. The deep learning method also solves the two major problems of traditional image segmentation to a certain extent: green interference and image exposure. However, our data set is small. Augmenting the data set is essential for further improving the performance and generalizing on other crops. Also, FCN-2s is a pixel-to-pixel learning model, which does not consider the association among pixels. Therefore, using an advanced network to deal with complex data set is considered first.

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