A Quantitative Analysis Method of Soybean Leaf Based on Key Point Detection

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Abstract

Fast and accurate measuring and assessing phenotypic traits of soybean leaf play a key role in the soybean breeding. The manual analysis of soybean leaf is time-consuming and prone to human errors. In this paper, an automatic quantitative approach is proposed which can obtain the vital geometric parameters (e.g., major axis, minor axis, and tip angle) of soybean leaf based on key point detection model. Specifically, the proposed method utilizes the Stacked Hourglass Network to find and accurate localize the four key points of each soybean leaf. Once those interest points are identified, then the distances between them and the tip angle are computed automatically. By performing such strategy, the quantitative analysis of soybean leaf can be handled effectively. The extensive experimental results obtained on the collected soybean leaf dataset verify that the proposed method has better convergence accuracy and robustness than other classical methods.

Keywords—plant phenomics, deep learning, key point detection, stacked hourglass network.

Materials & Methods

A. Image Acquisition And Dataset Construction

In this study, we build a soybean leaf images dataset, consisting of 6,912 samples from 2,304 soybean leaf images for performance evaluation. All soybean leaves were sourced from the experimental field north of South China Agricultural University in Guangzhou.

1) Dataset acquisition and construction:

We planted soybeans in the experimental field twice at different times, and obtained mature soybean leaves through two collections. A total of 2,304 soybean leaf data were obtained from the two collections of leaves, of which 400 data were used as the testing set, and the rest were used as the training set. Then the collected leaves were scanned into RGB images into the computer. Fig. 1 presents some samples of the soybean leaves dataset. In order to construct a training set, we developed a key point annotation tool based on python to label leaf images.

2) Definition of key points and geometric parameters:

We have defined 13 key points for each image, one of which is at the junction of the three leaves, and others are at the leaves. A soybean leaf has 4 key points: basal(A), apex(B), left(C), and right(D). The line between the two former points is the major axis, the line between the latter points is the minor axis, and the angle of CBD is the tip angle of the leaf. A sample is shown on Fig. 1.

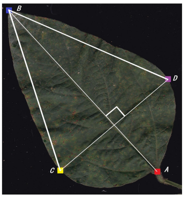

Fig. 1: The definition of key points and geometric parameters.

B. Key Point Detection

The CNN model used in this paper is the Stacked Hourglass Network which utilizes multiple layers of convolution features at the same time, making use of semantic information. The training speed and effective key point detection of the Stacked Hourglass Network are the primary reasons that we use this network. The illustration of the two Stacked Hourglass Network is depicted in Fig. 4(a).

1) Stacked Hourglass Network:

a) Single Hourglass Module: The overall Hourglass Network is composed of a single Hourglass Network module (shown on Fig. 2b) in series. First, the convolution layer and the max pooling layer scale the features to a small resolution. After obtaining the smallest feature map (4×4), the network starts up-sampling and gradually combines feature information of different scales. Here, the feature of lower resolution adopts nearest neighbor up-sampling, and two different feature sets are added element by element. After getting the output resolution, two consecutive 1×1 convolutions are followed for the final detection. The final output of the network is a set of heatmaps used to predict the probability of each key point in each pixel.

b) Intermediate Supervision: The core structure of the network is to stack multiple hourglass modules. The main idea of this process is to Predict the intermediate heat map and let the intermediate heat map participate in the loss calculation. Illustration of the intermediate supervision process is shown on Fig. 4(c). The network splits and products a set of heatmaps (outlined in blue)

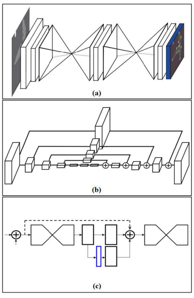

Fig. 2: An illustration of the Two Stacked Hourglass Network(a), A single hourglass network (b), the intermediate supervision process(c).

c) Training Details: The proposed framework is implemented with the Pytorch Library. We define the Mean Squared Error (MSE) as the loss function and train the framework using the SGD solver with a train batch size of 6, weight decay of 0 and momentum of 0. The initial learning rate is set as 25−4 and it is divided by 10 between epoch 60-90. Refer to the paper for detailed training parameters.

2) Related Functions:

a) Length Measurement: Given two points P1 and P2, the Euclidean distance of the P1 and P2 as the measurement of the length.

$$d = \sqrt{(x1 - x2)^2 + (y1 - y2)^2}$$

b) Angle Measurement: First we calculate the lengths among 3 points of a triangle, side b, c and d. Then calculate the angle as ∠CBD using 3 sides of length (Fig. 1 can be used as a reference).

$$\theta = \arccos\left(\frac{c^2 + d^2 - b^2}{2 \times c \times d}\right) \times \frac{180^\circ}{\pi}$$

Experiment

A. Detection Results

The testing set in this experiment includes a total of 400 images of soybean leaves. 3.75% of the images in the testing set perform not well in key point detection, which will be discussed later in Error Analysis.

To find the point localization accuracy, we first compute the Euclidean distance between the automatically detected key points and the ground true location (deviation in pixels). We hence also report the deviations normalized by the length (in pixels) of the relevant distance measured (major axis, minor axis). The results can be seen in Table I. The point average deviation is between 1.8% and 4.9% of the length measured on two different resolutions of images.

TABLE I: Detection Results On Key Points

4960×7015	***Pixel error***			***Relative error***		
keypoint	μ	σ	SE	μ	σ	SE
Leaf basal	44.09	29.36	1.09	0.019	0.013	0.0005
Leaf apex	41.91	23.40	0.82	0.018	0.011	0.0004
Leaf left	62.50	36.38	1.27	0.049	0.036	0.0013
Leaf right	61.59	37.44	1.31	0.048	0.031	0.0011
2480×3507	***Pixel error***			***Relative error***		
keypoint	μ	σ	SE	μ	σ	SE
Leaf basal	20.11	10.26	0.57	0.018	0.011	0.0006
Leaf apex	20.13	10.86	0.60	0.017	0.010	0.0006
Leaf left	30.14	18.13	1.00	0.042	0.025	0.0014
Leaf right	31.46	17.87	0.99	0.044	0.027	0.0015

[a] Key point detection error – Euclidean distance between ground truth and detected key points.
[b] SE denotes standard error.

After obtaining the key points, we use them to calculate the major axis, the minor axis and the leaf tip angle. Table II shows the estimation deviations for each geometric parameter measured. It can be seen that although the deviation of the tip angle is slightly higher than other two tasks, the accuracy of the tip angle measurement along with the major axis and the minor axis can still be considered to have the better accurate and effective results than manual measurement.

TABLE II: Detection Results On Geometric Parameters

4960*7015	***Error in cm***			***Relative error***		
parameter	μ	σ	SE	μ	σ	SE
Leaf Major axis	0.16	0.14	0.005	0.016	0.014	0.0005
Leaf Minor axis	0.13	0.10	0.004	0.023	0.020	0.0007
	Error in degree					
Leaf tip angle	1.49	1.32	0.045	0.034	0.029	0.0010
2480*3507	***Error in cm***			***Relative error***		
parameter	μ	σ	SE	μ	σ	SE
Leaf Major axis	0.14	0.10	0.005	0.013	0.010	0.0006
Leaf Minor axis	0.13	0.11	0.006	0.022	0.019	0.0010
	Error in degree					
Leaf tip angle	1.65	1.30	0.072	0.033	0.024	0.0013

[a] Key point detection error – Euclidean distance between ground truth and detected key points.
[b] SE denotes standard error.

C. Detection Examples

Fig. 7 presents successful detection examples on soybean leaves. As can be seen, after being detected and visualized, the corresponding key points are basically overlapped and there will not be obvious deviation between two points. Meanwhile, with careful observation, it is possible to notice the fact that the left and right key points on the soybean leaves have bigger chance to get the larger deviation. The reason is that the edges of soybean leaves do not have such obvious features. We believe that increasing the size of the training dataset may help to improve the accuracy of key point detection at the edge of the leaves to a certain extent.

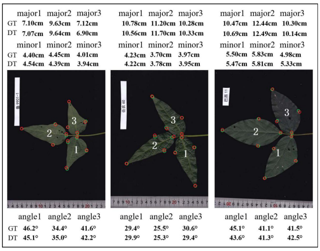

Fig. 7: Detection examples on soybean leaves. The ground truth key points are marked green, and the red marks the detected key points.

Conclusion

In this paper, we develop a method for measuring soybean leaf geometric parameters based on key point detection. The approach is tested in several specific tasks: key point detection on leaves, the measurements of the major axis, the minor axis and the tip angle in soybean leaf. The results show that the proposed method separately obtains the key point average deviation of 1.8-4.9% of the length measured,1.3-2.3% deviation for leaf major axis and minor axis, and 3.3-3.4% deviation for leaf tip angle of the true angle measured. With all experimental results demonstrated above, conclusions were drawn as follows: i) The Stacked Hourglass Network is able to learn features of soybean leaves automatically and gives outstanding results of key point detection. ii) The proposed quantitative analysis method is feasible and most current measurement of the soybean leaves can be done by it.

Main Reference

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