Accuracy Analysis of Plant Segmentation Network With Hue-enhancement

Baozhong Tian
Department of Mathematics and Computer Science
Bemidji State University, Bemidji, MN 56601
Baozhong.Tian@BemidjiState.edu

Abstract

In automated mechanical weeds control systems, accuracy of the segmentation of plants from weeds plays an important role to the economy of the operation. The detection rate and accuracy of localization of the plant stem are the two quantitative factors that determines the segmentation accuracy. A miss in detection may cause severe damage to the plant itself, and an inaccurate localization may still cause some damage to the plant.

In this paper, a YOLOv3 [Redmon and Farhadi, 2018] based CNN with hue-enhanced pre-processing was constructed for plant segmentation. The dataset, containing over 800 images of corn seedlings of various size taken at different stages of growth, was first annotated then trained and tested. The rate of detection and accuracy of localization are computed to compare with the results without pre-processing.

1 Introduction

As organic produces gain more and more popularity for health and sustainability concerns, mechanical weeds control has become an important field operation because of the harmful chemical used in herbicides with conventional farming practices. Traditional methods such inter-row cultivating only achieves about 50% effectiveness. Intra-row weed control, is even harder to achieve satisfaction with current implements [Forcella, 2000]. There have been research efforts [Hamuda et al., 2016] [Khedaskar et al., 2018], on segmentation of different part of a plant, using color information, often combined with machine learning techniques, to achieve relative higher rate of precision in segmentation. The goal of this research is to investigate segmentation techniques that are feasible for real-time applications to locate plant stems for intra-row weeds control.

Figure 1 shows the overall network architecture of Darknet-53, as described in [Redmon and Farhadi, 2018]. The network contains 53 convolutional layer, hence the number 53.

	Type	Filters	Size	Output
	Convolutional	32	3 × 3	256 × 256
	Convolutional	64	3 × 3 / 2	128 × 128
1×	Convolutional	32	1 × 1	
1×	Convolutional	64	3 × 3	
1×	Residual			128 × 128
	Convolutional	128	3 × 3 / 2	64 × 64
2×	Convolutional	64	1 × 1	
2×	Convolutional	128	3 × 3	
2×	Residual			64 × 64
	Convolutional	256	3 × 3 / 2	32 × 32
8×	Convolutional	128	1 × 1	
8×	Convolutional	256	3 × 3	
8×	Residual			32 × 32
	Convolutional	512	3 × 3 / 2	16 × 16
8×	Convolutional	256	1 × 1	
8×	Convolutional	512	3 × 3	
8×	Residual			16 × 16
	Convolutional	1024	3 × 3 / 2	8 × 8
4×	Convolutional	512	1 × 1	
4×	Convolutional	1024	3 × 3	
4×	Residual			8 × 8
	Avgpool		Global	
	Connected		1000	
	Softmax			

Figure 1: Network architecture of Darknet-53 as described in [Redmon and Farhadi, 2018]

.

Previous work on plant segmentation [Tian, 2019] showed qualitatively that the chance of detection got improved when enhanced with hue values that corresponds to the plant being processed. This paper will compare quantitatively the two accuracy factors to measure the potential improvements when using pre-processing techniques such as hue-enhancement on the input images.

2 The Experiments

The Darknet-53 network was implemented with Tensorflow 2.0 as described in [Zhang, 2019]. The original code was modified to make it compatible with the training and prediction of single class samples.

The experiments focus on segmentation of stems of corn seedlings. The images were taken over two planting seasons: The first batch of pictures were taken in 2017 in Wisconsin, and the rest were taken in 2019 in Minnesota.

2.1 The Images

Figure 2 shows two samples from the two batches of corn seedling images. The rectangle image on the left was taken in 2017, the square image on the right was taken in 2019.

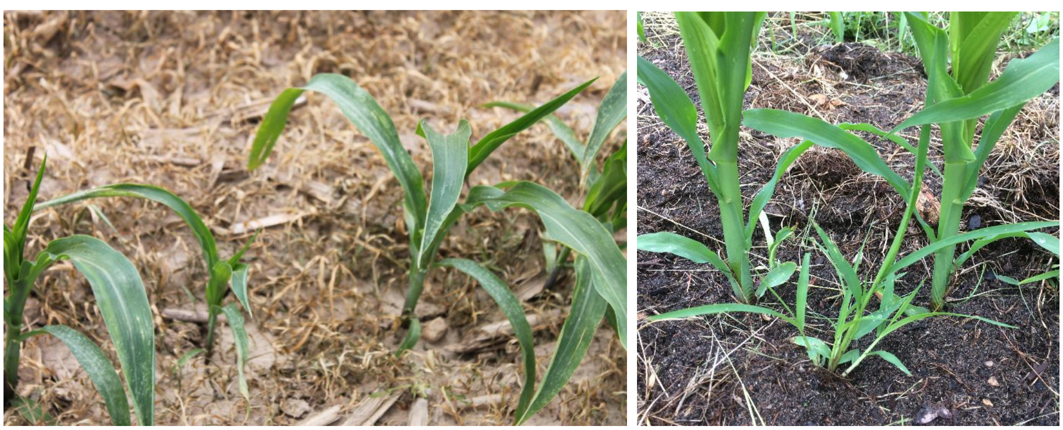

Figure 2: Samples from the two batches of corn seedling images. The one on the left was taken in 2017, the one on the right was taken in 2019.

The two batch of images show different aspect ratio, because the batch in 2017 was taken using a DSLR camera, and the batch in 2019 was taken using iphone in square image mode.

2.2 Hue Enhancement

To compare the difference of segmentation between the two experiments with and without hue enhancement, the images used in training and validation were processed with their saturation emphasized for the regions where the hue values fall within the hue range of green color of corn seedling. The saturation values are doubled when the hue values are between 45 and 105, which were determined by observing the hue range of the sample images. Different plants may show different range of hue values. The current lower and upper bounds of hue values seems to work well with corn seedlings. Figure 3 shows the hue-enhanced images of Figure 2.

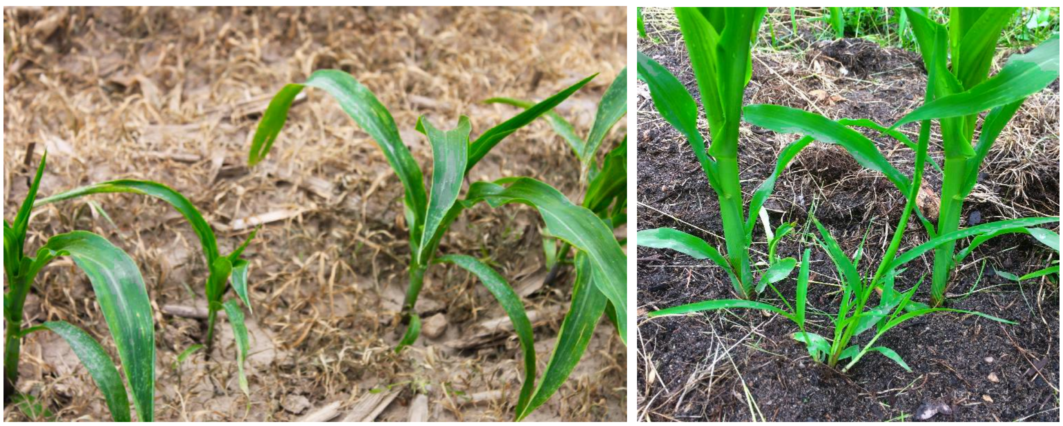

Figure 3: Samples from the two batches of corn seedling images with hue enhanced. They are corresponding images for images in Figure 2.

Please compare Figure 2 and Figure 3 for the difference in the colors. With hue enhancement, the green got greener, which make their color feature stand out better from the background.

2.3 The Trainings

The 825 corn seedling images were annotated with bounding boxes of corn stems. There are total of 1105 corn stems, 865 of which are used for training and 240 of which are used for validation. Figure 4 shows the annotated images with bounding boxes for corn stems.

The two set of images, one set with hue enhancement, and the other set without, were trained separately, which results in two set of weights for the network. The trainings did not start from random weights. A pre-trained YOLOV3 weights were used as starting point. Although the original 80-class weights does not contain corn stem class, it was used nonetheless to perform transfer training for this one-class model. Both training converged successfully within 50 epoches.

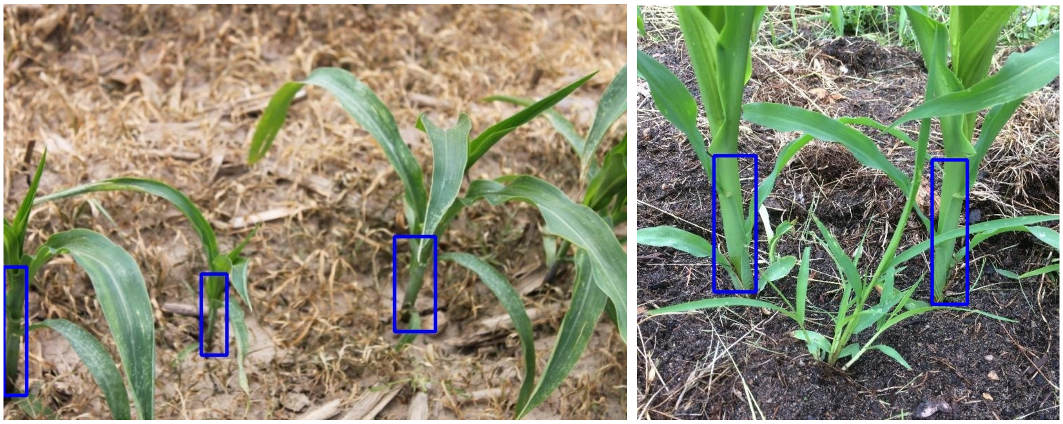

Figure 4: Samples from the two batches of corn seedling images with stems labeled. They are corresponding images for images in Figure 2.

2.4 Results and Discussions

There were two experiments: Firstly, training was carried out with original images, then detect on original images without hue enhancement. Secondly, training was carried out with hue enhanced images, then detect on hue enhanced images. A third experiment of detection on hue-enhanced images with non-enhanced network was a failure because it showed inferior on both the detection rate and accuracy of localization. This is to be expected because the training set was not optimized for hue-enhanced images. The result of the third experiment is not shown here. Figure 5 shows some samples from the two experiments. Both experiments showed some miss on detection. The experiment with hue enhancement did show higher detection rate and higher classification scores.

The accuracy of localization is for horizontal direction only because the horizontal location is what will be used when making the decision to cultivate or not. The Intersect Over Union (IOU) values are there for reference only because they are all pretty high, indicating a rather good fit on the bounding boxes detected. Table 1 shows the results of the two experiments mentioned above.

Training and Detection method	Detected stems	Total stems	Detection Rate	Accuracy of Localization	IOU
Without hue enhancement	169	240	70.42%	0.323%	0.963
With hue enhancement	190	240	79.17%	0.358%	0.954

Table 1: Table shows the results of the two experiments.

The detection rate gained an improvement of nearly 9% for the hue-enhanced

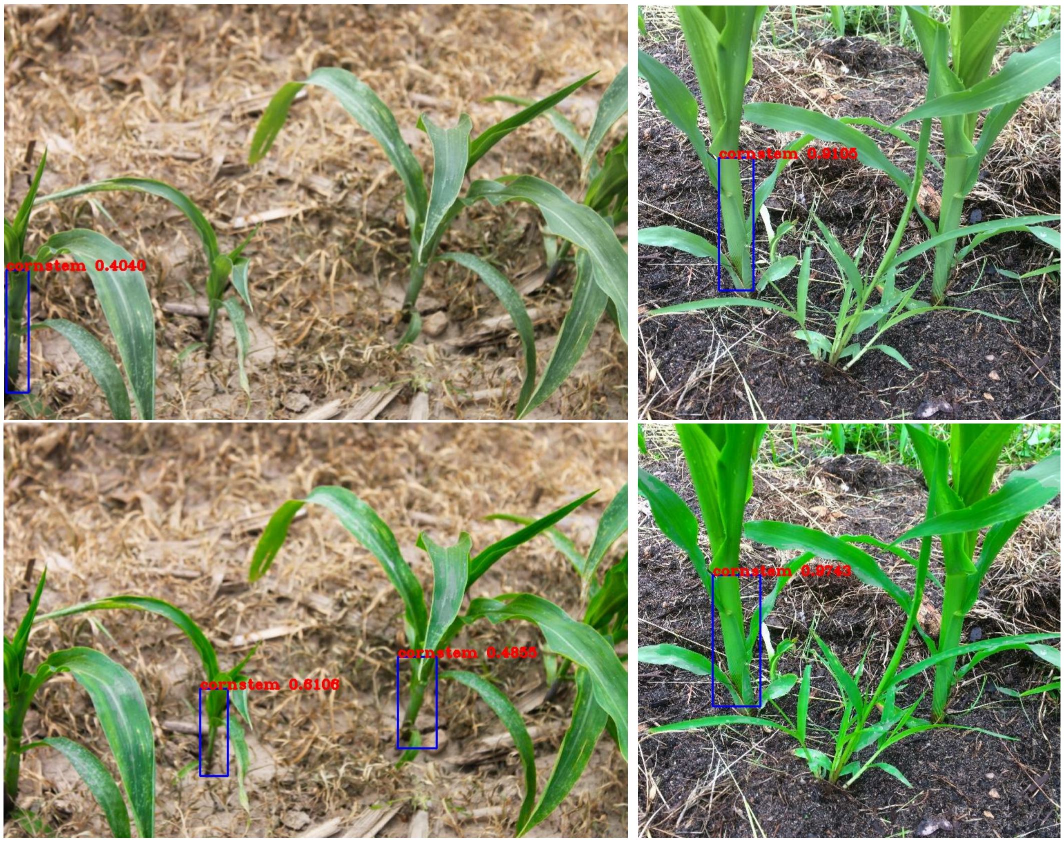

Figure 5: Comparison of the two experiments. The top two image are the results without hue enhancement. The bottom two images are the results with hue enhancement.

test images when training was done on the hue-enhanced images. The accuracy is slightly lower but not by much because they are both in the 0.32%-0.36% range, which is still quite accurate for practical purposes. The detection rate is considered to be more critical because any improvement means a lot of plants may get saved instead of being treated as weed and destroyed.

3 Future Work

The detection rate with hue-enhanced pre-processing, could still use some improvement to make the system practical in real-world organic farming practices. The plan include acquiring more realistic images and perform more training and testing. Better computation equipments such as high performance GPUs are to be acquired in the future to facilitate the training tasks.

References

[Forcella, 2000] Forcella, F. (2000). Rotary hoeing substitutes for two-thirds rate of soil-applied herbicide. *Weed Control*, 14(2):298–303.

[Hamuda et al., 2016] Hamuda, E., Glavin, M., and Jones, E. (2016). A survey of image proessing techniques for plant extraction and segmentation in the field. *Computers and Electronics in Agriculture*.

[Khedaskar et al., 2018] Khedaskar, S. V., Rokade, M. A., Patil, B. R., and N., T. P. (2018). A survey of image processing and identification techniques. *VIVA-Tech International Journal for Research and Innovation*, 1(1):1–10.

[Redmon and Farhadi, 2018] Redmon, J. and Farhadi, A. (2018). Yolov3: An incremental improvement. *arXiv*.

[Tian, 2019] Tian, B. (2019). Hue-assisted convolutional neural network (cnn) for plant stem segmentation. Paper presented at Midwest Instruction and Computing Symposium (MICS2019), April 5-6, 2019, Fargo, ND.

[Zhang, 2019] Zhang, Z. (2019). Yolov3 implemented in tensorflow 2.0. `https://github.com/zzh8829/yolov3-tf2`.