Smart Sprayer for Precision Weed Control Using Artificial Intelligence: Comparison of Deep Learning Frameworks

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Abstract

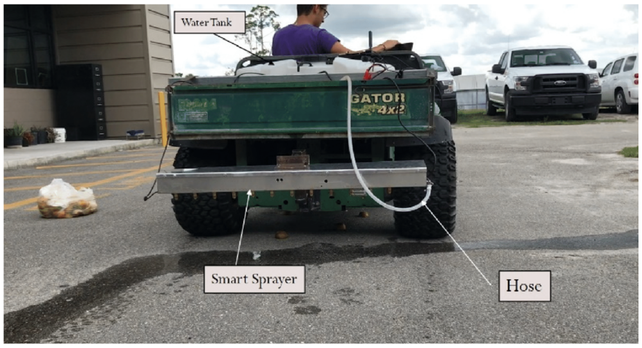
In this paper, comparison of deep learning-based target detection methods is presented for precision weed management system. Conventional weed control methods are to spray herbicides uniformly in every fields. However, it is intimately related with massive herbicides consumption, environmental issues and agrochemical residues on food product. Hence, an autonomous and intelligent herbicide sprayer has been developed with machine vision in order to determine the type of weeds in real-time and spray the proper herbicide only on desired spots. This paper presents a comparison of deep learning frameworks with evaluation metrics; Precision and Recall. Through this comparison, the smart sprayer system will be developed with more precise real-time target detection performance.

Introduction

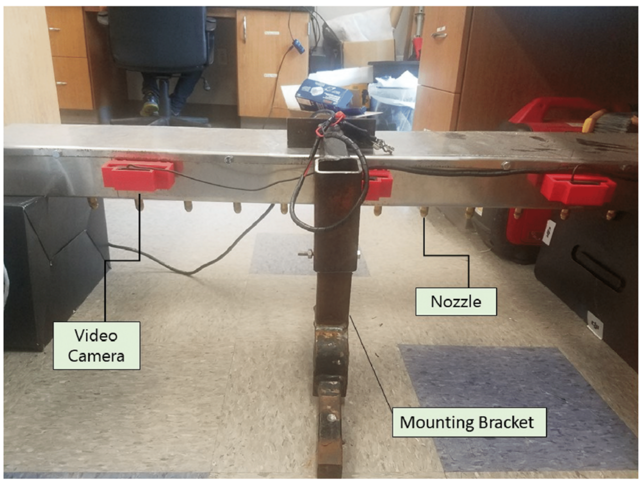
Since Weed control is closely related to crop yields, it is important to eliminate weeds in agriculture (Rajcan, Chandler, and Swanton 2004; Zimdahl 2018; Clements et al. 2004; Gianessi 2013). Weeds impede growing progress of the crop by depriving of light and the essential resources (e.g. water and nutrients). Once weeds are not removed at the proper period, the yield potential can be negatively impacted.

In order to control weeds, United States farmers sprayed about 113.36 million kg of herbicides (glyphosate) in 2014 (Benbrook 2016). Global herbicide market shows that farmers sprayed a total of 746.58 million kg of herbicides (glyphosate) worldwide in 2014 (Benbrook 2016). This enormous consuming number of herbicides is mostly due to the conventional spraying strategy, spraying herbicides uniformly in every area of fields. Since weeds usually occur in patches, conventional spraying strategy is not efficient in terms of cost and method. In addition, indiscriminate herbicide spraying causes environmental issues (e.g. soil and water contamination) and agrochemical residues on food products. The United State government warns regarding effects of herbicides on human health and environment (US Environmental Protection Agency; US Fish and Wildlife Service). Furthermore, there is an issue of a shortage of farm labor and increased costs for weed control (Duke 2012). Hence, developing autonomous and intelligent herbicide sprayer is required to reduce these negative impacts.

In recent decades, there has been a constant increase of interest in pest and disease detection (Cruz et al. 2017; Abdulridha et al. 2018; Cruz et al. 2019) and autonomous sprayer for controlling weeds (Moller 2010; Fernandez-Quintanilla et al. 2018), concluding that computer vision technologies will lower workload and costs in agricultural field. Using computer vision helps a smart sprayer system to have the ability to determine the type of weeds in real-time and spray the proper herbicide only on desired spots. In (Hong, Minzan, and Qin 2012), various sensors and techniques are surveyed for a smart sprayer analyzing machine vision, spectral analysis, remote sensing and thermal images. (Wendel and Underwood 2016) present classification of crops and weeds using spectral images, and it showed good performance. A spectral camera, however, has disadvantages that it is too expensive and has heavy computation load comparing to a RGB camera. There is also literature supporting the use of RGB images for weed detection. Weed detection is performed using Convolutional Neural Networks (CNNs), and weeds among grass and broadleaf are classified in (dos Santos Ferreira et al. 2017). Even though there is no contribution for a smart sprayer, it showed satisfying performance results. A herbicide sprayer using a RGB camera is developed for wild blueberry in (Esau et al. 2018). In this paper, weeds are determined using the color contrast



(a)



(b)

Figure 1. (a) The smart sprayer mounted on an All-terrain vehicle (ATV); (b) main components of the smart sprayer.

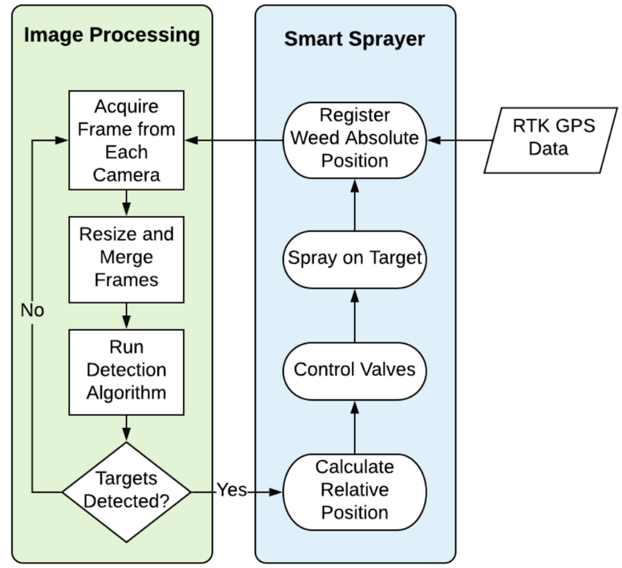


Figure 2. Overall workflow of the smart sprayer system.

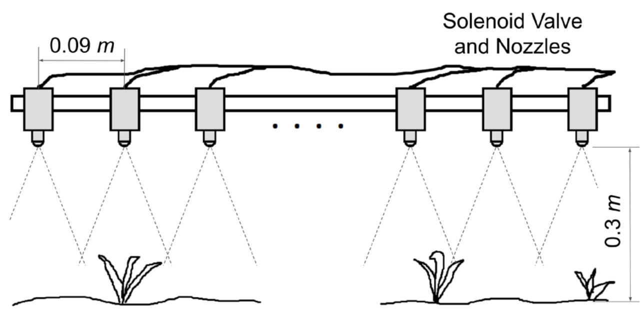


Figure 3. Nozzles arrangement design.

between the green weeds and the wild blueberry plants and soil surface which shown in reddish-brown background color. The image processing used in this paper is a low-level object detection strategy, and this method is limited only to certain wild blueberry farms.

In this paper, we present a comparison of deep learning-based target detection frameworks for a low-cost and smart precision sprayer system. In order to detect weeds, machine vision and deep learning-based target detection are applied to the developed system. In the next section, we present materials and method for the smart sprayer system, then three applications of deep learning-based target detection are compared and evaluated in Experiment Section. Finally, we present the conclusion and future works at the end of the paper.

In this paper, a comparison of deep learning-based target detection frameworks is presented for a low-cost and smart precision sprayer system (previously developed by Partel et al., 2019). In order to detect weeds, machine vision and deep learning-based target detection were applied to the developed system. In the next section, we present materials and method for the smart sprayer system; then, three applications of deep learning-based target detection were compared and evaluated.

Materials and Methods

A prototype of the smart sprayer system consists of individual nozzle control (12 nozzles with an adjustable spraying cone and 12 valves), a low-cost pump, a Real-Time Kinematic GPS (RTK-GPS), three video cameras (Webcam Logitech c920), speed sensor (odometer and laser-based sensor), and several relay boards, tubes, pressurized manifolds, etc. (Partel et al. 2019).

Hardware Description

Fig. 1 presents the smart sprayer attached on an All-Terrain Vehicle (ATV) through a hitch, and the workflow of the smart sprayer system is depicted in Fig. 2.

The nozzles arrangement is designed considering a work length of 1.08 *m* to be covered by sprayers. It employs

Figure 4. Tank and pump.

twelve nozzles to spray a width of 0.09 *m* each from 0.03 *m* of height as shown in Fig 3.

In order to spray herbicide rapidly and precisely after receiving signals from the main computer, a 95 *L* tank was utilized to store herbicide with a 4.10 *bar*, 8 *L/min* pump (FIMCO LG-25-SM, North Sioux City, SD, USA) as shown in Fig. 4.

12 *V* solenoid valves (WALFRONT 2 V025, China), with a response time of less than 50 *ms*, were utilized in order to control nozzles (TEEJET 5500-X5 Glendale Heights, IL, USA). Three nozzles can be adjusted by changing the angle of the spraying cone.

For the image acquisition system, three low-cost cameras (LOGITECH c920, Newark, CA, USA) were utilized. The cameras cover the work length of 1.08 *m*. The three cameras were installed to minimize an overlap.

For the positioning system, a RTK GPS (TOPCON HiperXT, Tokyo, Japan) was used with a 2.50 *Hz* update rate. Using the position data, a heading angle is also calculated to obtain accurate geo-locations of the targets on the soil.

The main computer unit utilized was a graphical processing unit (GPU) (NVIDIA GTX 1070 Ti, Santa Clara, CA, USA) with 2432 CUDA cores on a clock frequency of 1607 *MHz*. This GPU has 8 *GB* of memory.

The future overall goals of this project can be described as shown in the following;

1. Develop further a low-cost, high throughput, and smart technology to simultaneously scout and spray a variety of weeds with different herbicides.
2. Develop low-cost and multi-crop autonomous vehicles equipped with the precision spray technology.
3. Design and develop a high-level task planning and control system for the autonomous precision sprayers.
4. Conduct comprehensive economic analyses of the proposed multi-robot system.

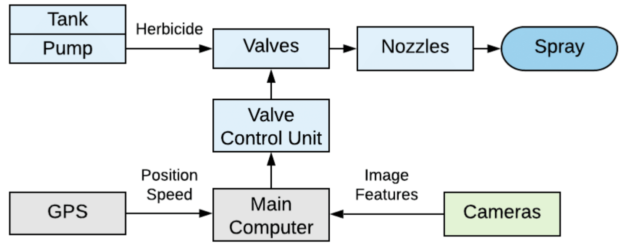


Figure 5. Hardware components of the smart sprayer.

Smart Sprayer Software

A software was developed to achieve a precise spraying on the target and to develop a weed map. The software can process up to 28 fps (frames per second) in all the steps in real-time. Fig. 5 depicts the overall workflow of the smart sprayer system.

Image Acquisition

Three cameras simultaneously provide the software of frames of resolution 640 x 480 pixels each. The obtained images are then merged as one single image of a 1920 x 480 pixels, which is then resized for a 1024 x 256 pixels final image. The final image was found to be a proper size to achieve real-time processing speeds. The cameras are limited to acquire up to 30 fps. The overall processing speed is determined by the network utilized and the capabilities of the GPU.

Target Detection

For the real-time target (object) detection, two frameworks were tested: (i) Faster R-CNN, and (ii) YOLOv3 (Redmon and Farhadi 2018). A primitive approach of target detection takes different regions of interest from the image, and it utilizes a CNN to classify the presence of the object within that region. The problem, however, is that the objects of interest might have various locations and scales in the image. Since the algorithm must select every region over the entire image, a computational load can be naturally increased. Hence, such an algorithm like R-CNN and YOLO have been developed in order to detect the target fast.

Convolutional Neural Network and Deep Learning

When considering a network of the object detection frameworks, Faster R-CNN and YOLO employs CNNs to train and detect objects. The name of CNNs is from a mathematical operator, convolution, and CNNs consist of three layers; input layer, output layer, and hidden layers. A typical CNN

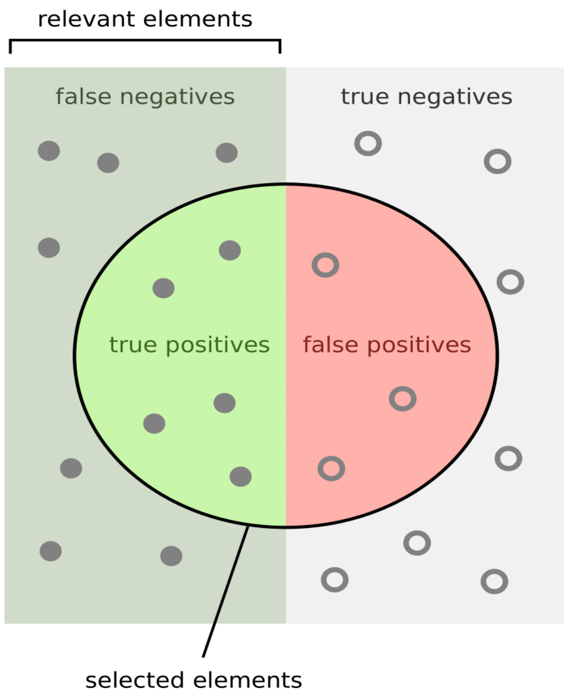


Figure 6. Precision and Recall.

has four main operations known as convolution, non-linearity, pooling (sub-sampling) and classification.

Evaluation Metrics

In all experiments, the performance of the target detection was evaluated based on visual observations, determining whether the targets or non-targets are detected correctly. The output videos, which are the results of deep learning-based target detection using various frameworks, were used to validate and calculate evaluation metrics.

As the evaluation metrics, the precision and recall (Fig. 6) of the deep learning-based target detection are used. For each framework, precision and recall are defined as shown in the following equation.

$$Precision = \frac{TP}{(TP + FP)},$$
$$Recall = \frac{TP}{(TP + FN)}, \tag{1}$$

where TP is True Positives, and FP and FN represent False Positives and False Negatives, respectively.

Results and Discussion

In this section, we present experiment results of two different object detection frameworks for developing the smart sprayer. In order to compare performances, we apply Faster R-CNN with Resnet 50, Faster R-CNN with Resnet101, and YOLOv3 with Darknet53 for detecting one specific type of target weeds. We utilized three different artificial plants as shown in Fig. 7. In the experimental field, twenty target weeds were randomly placed, and six and three of non-target plants were also implanted, respectively.

Figure 7. Target weed and Non-target plant used in the experiment.

All networks used in this experiment were trained using 1821 images of targets and non-targets labeled manually for each target position on the images. After training the networks, the real-time target detection was performed with two frameworks mentioned above using two videos recorded between 2 PM to 3 PM in September 2019 on sandy soil. On video is recorded without shade disturbances, and other one is recorded with shade disturbances. The hardware system used in this experiment are described in the previous Hardware Description section.

The experiment results are shown in Table 1 and Table 2. The best performing network was Resnet50 achieving 100% in all metrics for both video experiments. YOLOv3 achieved the lowest metrics of all three but still performed well, struggling mainly with false negative detections on shade disturbance zones (Fig. 8).

Note that the significant difference in processing time (evaluated in frames per second) of YOLOv3 compared to the two other networks, 176.13% and 228.38% for Resnet50 and Resnet101, respectively. This optimized processing time, while still achieving fairly good detection results, makes YOLOv3 a viable solution for the network framework detection for real-time or near real-time smart sprayer.

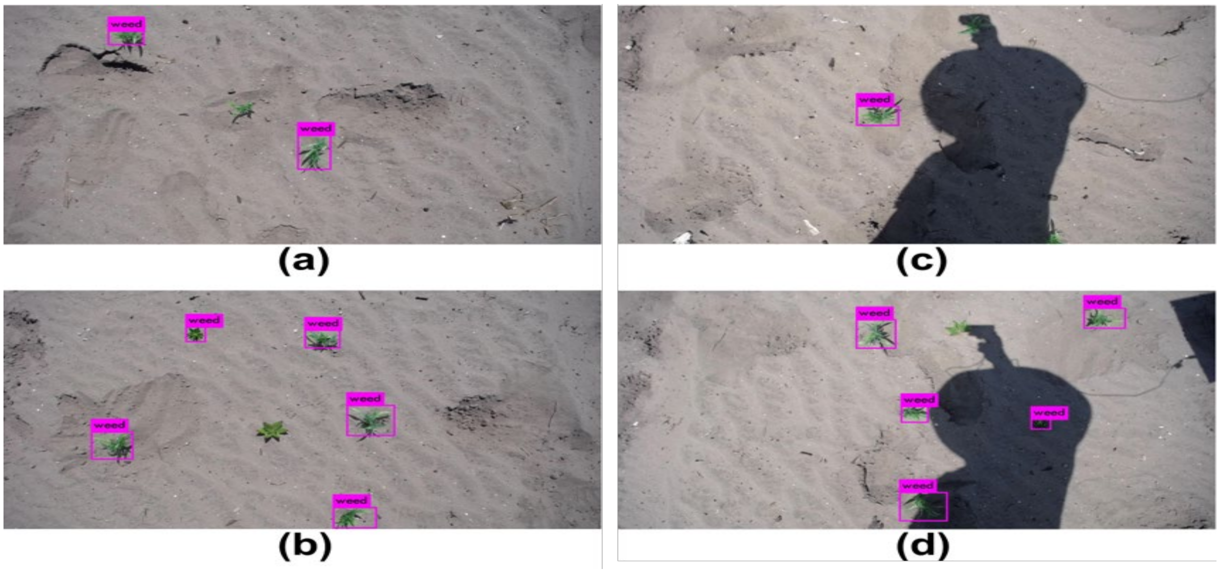


Figure 8. Experiment results of YOLOv3 without shade disturbances ((a) and (b)), and without shade disturbances ((c) and (d)). (a) One False Negative; (b) One False Positive; (c) One False Negative; (d) One False Positive.

Conclusion

This paper presented a prototype of the smart herbicide sprayer with machine vision in order to determine the type of weeds in real-time and spray the proper herbicide only on desired spots. For the machine vision part, performances of deep learning-based target detection methods are compared. We utilized two types of deep learning frameworks, Faster R-CNN and YOLOv3, and three types of networks, Resnet50, Resnet101 and Darknet53. After training all networks using 1821 images, experiments were carried out with two videos which is recorded one type of target weeds and two types of non-target plants in the field with and without shade disturbances. The experimental results showed the best performing network was Resnet50, and it will be successfully applied to the smart sprayer system for better performances.

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Table 1: Experimental results.

Framework	Network	Scale	FPS		True Positives	False Negatives	False Positives
Faster R-CNN	Resnet50	1248x708	5.405		20	0	0
				w/ Disturbances	20	0	0
Faster R-CNN	Resnet101	1248x708	4.545		20	0	0
				w/ Disturbances	19	1	0
YOLOv3	Darknet53	1248x708	14.925		18	2	2
				w/ Disturbances	17	3	2

Table 2: Precision and Recall.

Framework	Network		Precision	Recall
Faster R-CNN	Resnet50		100%	100%
		w/ Disturbance	100%	100%
Faster R-CNN	Resnet101		100%	100%
		w/ Disturbance	95%	100%
YOLOv3	Darknet53		95%	90%
		w/ Disturbance	85%	89.5%

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