132. AI-driven autonomous spraying for precision weed management in specialty crop production

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Abstract

Effective weed control in vegetable crops is crucial for optimizing yield and reducing herbicide use. This study developed a low-cost AI-driven robotic smart sprayer for targeting weeds in pepper and tomato crops on raised beds. Field tests evaluated its performance, with Tests 1 and 2 conducted on pepper and tomato beds, respectively. The sprayer achieved 89% and 88% precision, with missed targets below 5%. Recall was 86% and 84%, demonstrating effective real-time weed targeting while avoiding crops. Results highlight the sprayer's potential for precise, efficient weed control in vegetable fields.

Keywords: machine vision, object detection, precision agriculture, robotic weed sprayer, spraying system

Introduction

Robotic weed sprayers have been developed in the past two decades to improve precision spraying, reduce the amount of herbicide applied, and improve crop yield (Barbosa Júnior *et al.*, 2024; Vijayakumar *et al.*, 2023). Lee *et al.* (1999) developed a robotic weed sprayer for tomatoes, which used machine vision techniques and colour segmentation look-up tables to identify and differentiate the weed patch from the plants. The system identified 73.1% of tomatoes and 68.8% of the weeds in field trials. To prevent chemical drift while applying herbicides, researchers have tried applying the herbicide by mopping it directly to the surfaces of cut weeds using robotic arms (Chen *et al.*, 2005). However, since the herbicide concentration used was higher than the label recommendation, it could possibly result in non-target injury. Moreover, the experiments were conducted in a controlled environment and not in an actual crop field. In another study, a fully autonomous robotic system with a high-resolution camera, LiDAR, and GNSS was used for efficient weed mapping (Hansen *et al.*, 2013). It used multispectral cameras on airborne robots based on small-scale helicopters to capture field images, which were then analyzed by a ground-based system to identify the regions of weed presence. Partel *et al.* (2019despite the fact that distribution of weeds is typically patchy, resulting in wastage of valuable compounds, increased costs, crop damage risk, pest resistance to chemicals, environmental pollution and contamination of products. To reduce these negative impacts, a smart sprayer was designed and developed utilizing machine vision and artificial intelligence to distinguish target weeds from non-target objects (e.g. vegetable crops) developed an AI-enhanced weed sprayer attached to the back of a John Deere Gator. This sprayer was tested on artificial plants and real plants with real weeds, and its detection and spraying performance were evaluated. Although the spraying system performed well in detecting real targets (8% missed weed targets), the precision and recall for the spraying system were less than 80%.

Commercially developed weeding robots such as the 'BoniRob' developed by Bosch in collaboration with the Leibniz University of Hanover also exist. This system targeted weeds in carrot crops using mechanical actuators (Michaels *et al.*, 2012). Ecorobotix (Ecorobotix, Yverdon, Switzerland) was built for spot spraying of broad leaf weeds in meadows (Anken and Latsch, 2022). When tested at two different sites, it achieved a detection rate of 90% and 85% for broad leaf weeds and a spray coverage of 89%. Like most commercial systems, these commercial robotic weeding systems and their underlying technology are proprietary. Hence, there is a notable scarcity of publicly available technical information regarding the system design, decision-making algorithms, and performance metrics of these systems.

Considering the limitations of robotic herbicide sprayers developed by researchers and the restrictions of the commercial ones (Abdulridha *et al.*, 2023; Rui at al., 2024; Vijayakumar *et al.*, 2023), this study focused on developing a robotic smart sprayer for precision herbicide application using deep learning, a customized object detection model, and combining it with a robust spraying system to ensure uniform spray application on vegetable raised beds. A low-cost robotic smart sprayer was developed for detecting, localizing, and spraying three types of weeds (broad leaf, sedge, and grass) in vegetable crops (pepper and tomato). This robot could move over raised plasticulture beds and row middle and perform precision target spraying on weeds. The performance of the system was evaluated through the speed test of the algorithm and through two field tests (Test 1 and Test 2) on vegetable plasticulture.

Materials and methods

Robotic smart sprayer

The robotic smart sprayer is shown in Figure 1. It has a frame (1.78 m wide and 1.78 m long) built from aluminium extrusion tubes (40 mm by 40 mm). The sprayer's top hood covers all the electrical and electronic components, while the rear hood covers the pipes, nozzles, and other parts of the spraying system. The robotic smart sprayer used four 406.4 mm (16×6.5-8, 100 Nm) motorized wheels (UU motors; UU Motor Technology, Changzhou, P.R. China). A 60.56-litre sprayer tank (0.61 m×0.38 m×0.25 m) was mounted on one side of the robot, while a 48 V 100 A OGRPHY battery (OgrphyTech; Shenzhen, P.R. China) was mounted on the other side. This single battery source powers the robot and all the electrical and electronic components in the robotic smart sprayer. An RTK GPS (Sparkfun GPS-RTK-SMA; SparkFun Electronics, Niwot, CO, USA) sensor that provides a high accuracy location solution (RTK with 10 mm accuracy) was used for measuring the robot's speed.

The machine vision system includes a 1.6-megapixel industrial camera (DAHENG GetCamera, Daheng Group, Beijing, P.R. China) attached with a 5 MP (F2.0, 6mm) non-distortion lens. A Dell Alienware M16 R2 (Dell Technologies, Austin, TX, USA) laptop with an NVIDIA 4070 GPU was used to analyze the collected data in real time. The camera was mounted on the front side of the robot at a height of 1.27 m from the ground facing vertically downwards, covering a horizontal field of view (FOV) of 0.965 m. A multi-threaded Python code was implemented to get information from the camera and the GPS concurrently, while also processing the frames for nozzle information. The code used the input from the camera and sent the frames for processing to extract the class and location information using a customized object detection model. The system used a trained

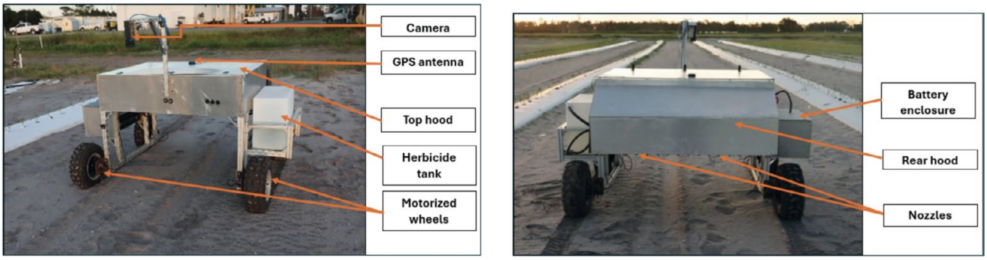

Figure 1. Robotic smart sprayer's front view (left) and rear view (right).

customized nano model of YOLOv8 (Ultralytics, 2024) for object detection. The trained detection model was converted to a TensorRT-based model to improve its real-time processing speed. The information from the machine vision system was transmitted to an Arduino MEGA 2560 (Arduino Inc, Italy) which triggered the opening and closing of the solenoids.

The spraying system and all its components (four pumps, proportional control valve, pressure gauge, solenoids, nozzles, pressure transducer, etc.) were mounted on the robot in a planned way to avoid being exposed directly to the external environment. The top hood covered the pumps and part of the pipes that led to the main pipe. The rear hood covered the main pipe, pressure gauge, hoses (which connect the solenoids to the nozzles), and sixteen nozzles. Figure 2 shows the arrangement of the components of the spraying system under the rear hood. A proportional integral (PI) control is used to maintain a set pressure in the system through individual control of pumps and the proportional control valve.

Performance evaluation

The performance evaluation for speed was done on the pepper beds in the fields of the Southwest Florida Research and Education Center (SWFREC). The experiments were performed post noon, and the robot traversed both rows in the same direction. The robot was moved at a speed of 2.41–3.22 km/h for all the tests and the time taken for the code to complete processing and exchange information with the threads and scripts was noted. For evaluation of the spraying performance of the sprayer two field tests – Test 1 and Test 2 – were conducted on raised plasticulture beds of tomato and pepper of the SWFREC. The beds used for testing are shown in Figure 3.

The spraying performance was evaluated based on the criteria presented in Table 1, while Table 2 presents the evaluation metrics used. After each trial in both tests, an expert inspected the sprays to assess spraying efficiency. The precision and recall of the spraying system were used as metrics for performance evaluation. The environmental conditions during Test 1 included sunny skies with moderate winds (35 km/h). For Test 2, it was sunny with clear skies and no wind. A total of 13 trials were conducted to evaluate the performance. Both the beds had a weed distribution mostly dominated by sedge with very few grass leaf weeds. Sedge and grass were distributed randomly on the bed surface and were the focus of these tests as opposed to the broad leaf weeds which grow on the edge of the beds. The tomato bed had a higher density of weeds on the bed surface as compared to the pepper bed.

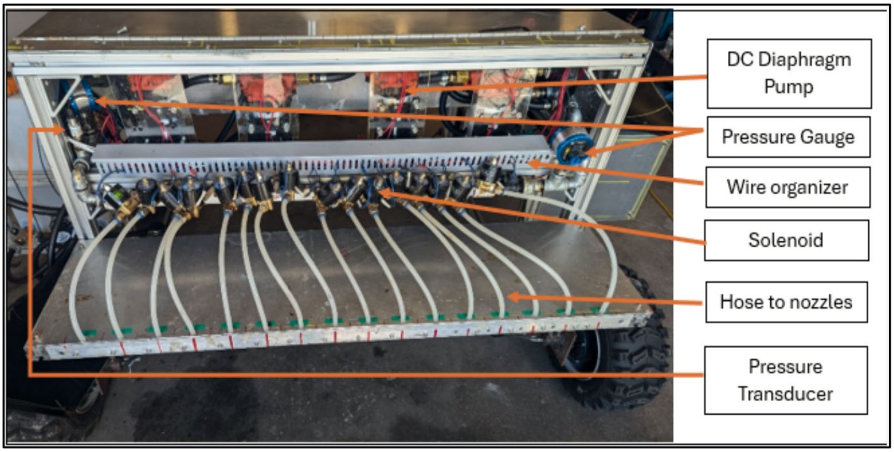

Figure 2. Parts of the spraying system under the rear hood of the robot.

Figure 3. The vegetable beds (marked in orange) used for the final test.

Table 1. Spraying performance evaluation scenarios.

Nomenclature	Description
Case 1 (C1)	Targets correctly sprayed
Case 2 (C2)	Imprecise spray, i.e., only a portion of the spray hit the target.
Case 3 (C3)	Sprayed but missed the target
Case 4 (C4)	No spray
Case 5 (C5)	Non-target sprayed (Not plants)
Case 6 (C6)	Plants sprayed

Table 2. Robotic smart sprayer performance evaluation metrics.

Metric name	Notation	Formula
Precision of the spraying system	P_S	$\frac{C1 + C2}{C1 + C2 + C3 + C5 + C6} * 100$
Recall of the spraying system	R_S	$\frac{\mathrm{C1} + \mathrm{C2}}{\text{Total number of targets}} * 100$
Missed spray	M_S	$\frac{\mathrm{C4}}{\text{Total number of targets}} * 100$

Results

Model performance: speed

The model's performance, in terms of the time taken for the entire main thread when tested in real-time on the pepper bed, is shown in Figure 4. It shows the speed for three trials, each containing results for 1500 frames. The tests had many instances of no detection and multiple detections in a frame. The loop times varied between 40 ms and 80 ms when there were detections in the frame (Figure 4). For zero detections (i.e. no classes of interest in the frame), the loop time varied between 15 ms to 40 ms. An increase in the average time taken per frame was observed when detections were present compared to when there were none. This is due to the model's process of extracting relevant features from the image and utilizing the bounding box data for subsequent tasks, such as nozzle actuation. Table 3 presents the average time taken per loop for different numbers of detections for the trials on the pepper bed. The average value for zero detection in the frame is 28.5 ms (for three trials). The average value increases to around 55 ms for one or more detections. It is important to note that loop times do not increase with the increasing number of detections beyond the first detection.

Table 3. Average time taken per loop for varying numbers of detections for the trials on the pepper bed.

	Time taken (ms) for varying number of detections							
	0	1	2	3	4	5	6	7
Trial 1	26.3	55.1	55.42	55.67	55.8	53.9	55.6	54.1
Trial 2	27.1	57.9	57.4	57.5	57.05	57.8	58.1	54.1
Trial 3	32.1	60	59.3	57.4	55.8	53.7	54.2	54.8

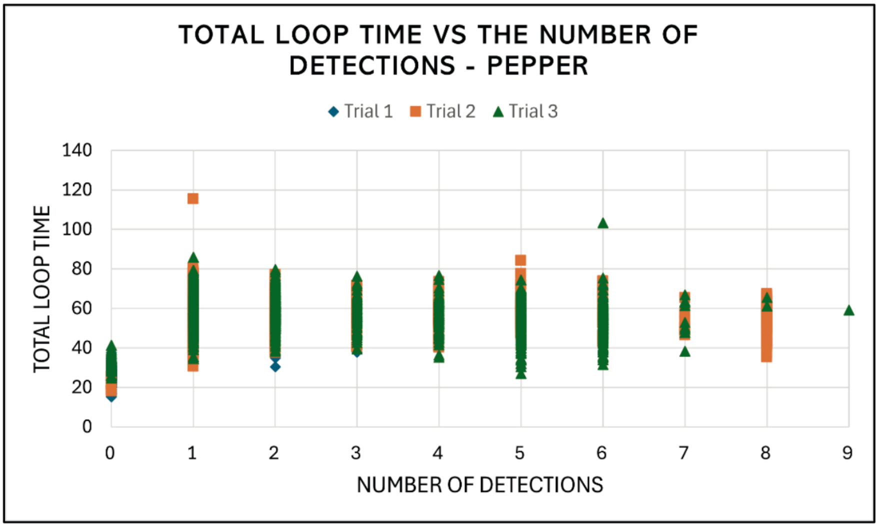

Figure 4. Speed of the main code in terms of the total loop time vs the number of detections per frame on the pepper bed.

Model performance: field tests

The real-time spraying was evaluated through field tests. The results of the spraying performance from Test 1 and Test 2 are presented in Table 4 and Table 5. For Test 1, the system achieved a precision of 89% and a recall of 86% in terms of the spraying performance. The system had a few missed targets but zero non-target sprays. More importantly, no pepper plants were sprayed in any of the trials, indicating high effectiveness in avoiding spraying on plants.

The tomato bed chosen for Test 2 had more weed targets. The system returned an average spraying precision of 88% and a recall of 84%. There were higher missed targets and imprecise sprays in this test as compared to Test 1. This can be attributed to a higher number of targets in the tomato bed and the presence of slightly older weeds with brown leaves causing missed detections. Like Test 1, there was no case of plants (i.e., tomatoes) being sprayed in Test 2 as well.

Discussion

Model performance: speed

Model performance, in terms of speed, evaluated on images collected by the robot in real-time test conditions, gave us an insight into the bottlenecks in real-time implementation. When there were classes of interest (three weed classes and two plant classes for the present case) in a frame, it was detected by the model, and the average loop time was around 55 ms. Without any detections, the loop time for trials was around 28 ms. The trials involved saving processed images for debugging, which increased the loop times by 12–15 ms. Without this step, the real-time loop times would be around 40–45 ms, resulting in a speed of 22–25 frames per second (FPS) for the code.

Table 4. Spraying performance results for Test 1.

Trial	C1	C2	C3	C4	C6	P_S	R_S
Trial 1	12	5	2	1	0	89%	85%
Trial 2	12	4	3	1	0	84%	80%
Trial 3	17	3	0	0	0	100%	100%
Trial 4	18	1	1	0	0	95%	95%
Trial 5	14	1	4	1	0	79%	75%
Trial 6	15	1	3	1	0	84%	80%
Average						89%	86%

Table 5. Spraying performance results for Test 2.

Trial	C1	C2	C3	C4	C6	P_S	R_S
Trial 1	30	7	4	1	0	90%	88%
Trial 2	28	5	7	2	0	83%	79%
Trial 3	24	9	7	2	0	83%	79%
Trial 4	30	9	2	1	0	95%	93%
Trial 5	29	6	5	2	0	88%	83%
Trial 6	29	7	4	2	0	90%	86%
Trial 7	31	4	5	2	0	88%	83%
Average						88%	84%

Model performance: field tests

The field tests demonstrated a good performance in detection and spraying accuracy in both tests. The system performed excellently in avoiding spraying on pepper and tomato plants. This is an excellent result as it shows the system's effectiveness in targeting only the weeds and preventing losses in crop yield due to incorrect identification and spraying. Certain cases of missed detection occurred due to fluctuations in the sunlight and the high contrast between the bed's surface and the soil next to it, creating a darker background for the weeds on the edge. While the missed detections were low in both tests, the case of no spray (C4) could be seen in both. This can be attributed to either missed detection or loss of information in the algorithm due to sync mismatch between the threads and the scripts that perform the actuation (i.e., triggering the nozzle). Imprecise spray (C2) is affected by a lot of reasons. Minor changes in the throttle input and direction of the robot cause a momentary spike in the speed values. This speed received from the GPS sensor is a critical parameter in determining the delay in nozzle activation, and sudden spikes can affect spray application performance even with a filter to smooth out the GPS sensor data. Additionally, the beds are not perfectly straight, as they have a few minor bends and curves. This forces adjustments in the direction of motion, causing fluctuations in the GPS values, which in turn affects spray timing. A better RTK GPS sensor and feedback control of the robot to adjust the motion could improve the spraying performance.

Conclusion

A robotic smart sprayer combining a machine vision system with a spraying system was developed and tested on pepper and tomato beds. The complete robotic sprayer and its sub-systems are described. Speed tests conducted to evaluate the overall speed of the machine vision algorithm gave a speed of 22–25 FPS. Field tests, which focused on the real-time spraying performance, returned high values for precision (89% and 88%) and recall (86% and 84%). No plant targets were sprayed in any of the tests. The missed targets were mostly due to fluctuations in environmental conditions, especially ambient light and wind, which affected the detection. The spraying performance of the system resulted in a few imprecise sprays and missed sprays owing to the complexity of the systems (multiple subsystems communicating with each other). Improvements in the code to sync the information interchange among the threads, as well as reducing the latency, can solve some of the issues. A better RTK GNSS module with less sensitivity to fluctuations in the motion of the robot and a better control algorithm for the robot to navigate the raised beds can improve spraying accuracy and precision in real-time applications.

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