Quadruped Robot Platform for Selective Pesticide Spraying

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Abstract

Effective control of disease and pest infection is vital for maximizing crop yields, and pesticide spraying is a commonly used method for achieving this goal. This study proposes a novel approach to selective pesticide spraying using a quadruped robot platform, which we tested in a broccoli field. We developed an algorithm to detect and track worms based on our proposed Histogram of Oriented Gradients and Support Vector Machine (HOG-SVM) techniques, integrated with the recent object detection and tracking methods. Our platform was tested by traversing the furrows between the broccoli crop lines and continuously scanning to detect cabbage worms. Our experiments demonstrate that the proposed HOG-SVM algorithm successfully reduced the false positive rate of real-time worm detection by reducing around 90% for the imitation environments and around 60% for the actual field.

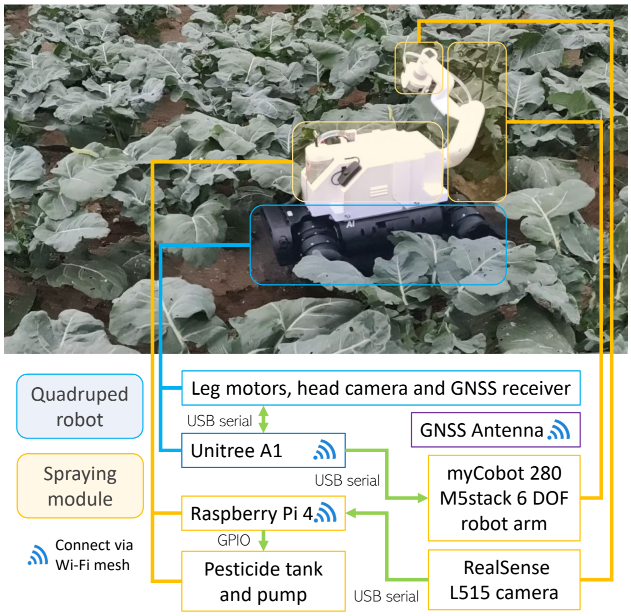

Figure 1. The quadruped robot scans for the worms on a raw broccoli field. The green arrows and the Wi-Fi mesh symbols denote the communication methods between different modules.

1 Introduction

Agriculture is a repetitive cycle of physical labor on cultivating crops with various dynamic factors like vegetation growth and weather. These criteria are suitable for automation applications using robot manipulation and computer vision algorithms. In recent years, there has been a growing trend in agricultural robot applications like soil monitoring [19], seeding [9], weed monitoring [10], pesticide spraying [15], and harvesting [14, 24, 1].

While every part of the steps is essential for crop production, our study focuses on automation for pesticide spraying tasks using robots and computer vision. Usually, pesticides are sprayed regularly and over the entire field to prevent pests and diseases. This has a significant impact on food safety as well as on costs due to spraying that is not originally needed. If pests can be automatically recognized and pesticides applied on an individual basis, these problems can be solved simultaneously.

In this paper, we propose a quadruped robot platform to operate in the outdoor field and to spray pesticides selectively with real-time worm detection. Figure 1 illustrates our platform working in a real broccoli field. Quadruped robots were proven stable and could maneuver in any terrain [6][3], which are difficult situations for wheel-type robots. We also developed a robust worm detection framework to deal with the shaky video frames taken by the camera attached to the end-effector of the robot arm. The contributions of our research are as follows:

1. We propose a quadruped robot platform with ba-

sic features of real-time control of locomotion, camera streaming, robot arm manipulation, and GNSS positioning.

2. We propose a worms detection framework that combines YOLO+Deepsort object tracker and HOG (Histogram of Oriented Gradients) -SVM classifier to reduce false positive cases effectively.

3. We implemented spraying modules using robot arm manipulation and worm detection for real-field applications.

2 Related work

2.1 Pesticide spraying robot

Unmanned aerial vehicles (UAV) using drones with pesticide tanks and sprayers are used in recent approaches for pesticide spraying [5, 7]. However, drone operations only allow uniform spraying from high positions, which limits pesticide options and increases the risk of excessive spraying due to unpredictable wind conditions. The more advanced method of robot platform for unmanned ground vehicles (UGV) primarily still uses wheels for locomotion and operates in a limited area, like a greenhouse on a particular track [2]. Bonirob was first built for wheat fungal phenotyping [17] and is now widely used for various agricultural tasks like mechanical weed control [22] and selective herbicide spraying [18].

2.2 Pest detection algorithm

One of the effective methods of selective pesticide spraying is to spray only into the insect infection area of the field. Researchers use image processing combined with environmental knowledge to detect insects. Johnny L et al. in 2014 [11] used image processing to convert RGB images into grayscale and calculate the difference of uniform color trap reference to detect the insects on paddy fields. Another method of a disease detection algorithm for selective grapevine spraying was done by Oberti et al. [13] utilizing spectral indices for fungal detection in infection tissue [12].

Recently, machine learning has been common for pest detection applications, especially when many features are believed to correlate with identification. Espinoza et al. [4] use artificial neural networks to detect and classify adult-stage whiteflies and thrip collected in sticky traps in a tomato greenhouse. Other researchers, Kasinathan et al. [8] performed both classical machine learning and deep learning using real field insect dataset provided by J. Wang et al. [20] and Xie et al. [23]. The classifications by CNN have accuracy above 90%, outperforming classical ML with only 80% accuracy.

3 Worm detection and spraying system

3.1 Robot platform configuration

Our robot platform consists of a quadruped robot and a spraying module, as shown in Fig. 1. To ensure the flexibility needed for maneuvering uneven soil and working closely with crops for pesticide spraying, we chose a quadruped robot as the central platform. The spraying module consists of a robot arm, a water pump, and an RGB-D camera mounted on the robot's end effector. External batteries have been added to power the pump and robot arm. The devices are covered by a specially designed and 3D-printed case to protect them from rain and dust.

All modules are connected via ROS under WiFi mesh. The remote operation program receives the robot sensor readings, like camera streaming images, and then processes the data to operate the spraying module. The robot arm is initially positioned towards the robot's side. When a pest is automatically detected, the operation program sends commands to control the robot arm by inverse kinematics and a spraying signal to spray the pesticides.

3.2 Worm detection and tracking

In order to effectively eliminate the cabbage worm, the most prevalent pest in the broccoli field, we have developed a real-time worm detection and tracking system to identify the target area for pesticide spraying accurately. An overview of the pipeline of this system can be seen in Fig. 2. Since missing pests is the most critical situation to avoid, the system should be configured to detect as many candidates as possible. However, this will result in many false positives (FPs), so a classifier is introduced to remove FPs effectively. Therefore, we propose to introduce HOG-SVM (Histogram of Oriented Gradients and Support Vector Machine) approach to the framework focusing on the contour features instead to account for the similarities in color between the leaves and the cabbage worms. This conventional method is chosen to focus on a shape-based descriptor filter with limited computation power on the platform. Our experiments demonstrate that HOG-SVM filters significantly improve detection reliability with a marginal increase of just 0.5% in total inference time.

We utilized YOLO [16] as the worm detector to ensure a timely and efficient process: $\Theta_{\mathrm{YOLO}} : I \to \Omega$. I is an input image. Ω is a set of extracted objects' bounding boxes $\mathbf{b}$ with a confidence value c: $\Omega = \{\mathbf{b}_i, c_i\}(i = 1, ..., n)$, where n is the number of detected objects. The detection results whose confidence values lower than predefined c_{th} are then refined through HOG-SVM: $\Theta_{\mathrm{SVM}} : H(I, \mathbf{b}) \to d \in \{0, 1\}$. Θ_{SVM} returns a binary classification result d. H converts the detected region to the HOG features while

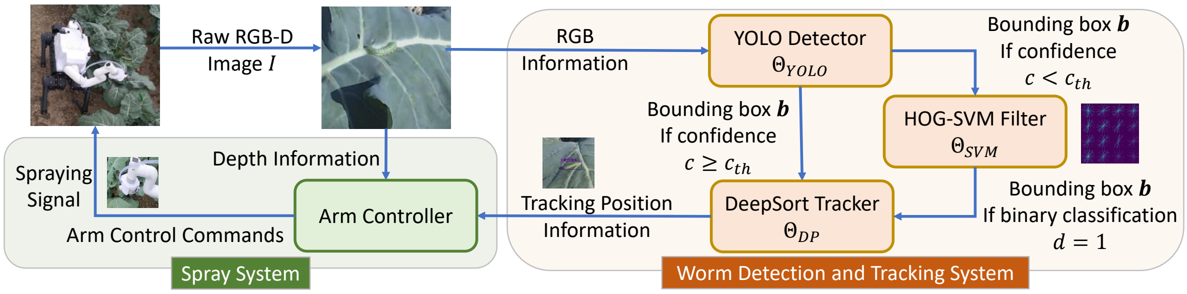

Figure 2. Worm tracking and pesticide spraying workflow overview

Figure 3. Training dataset samples

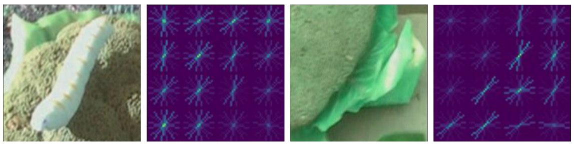

Figure 4. HOG features extraction: True positive worm and false positive leave boundaries

Figure 5. Tracking results on real worms

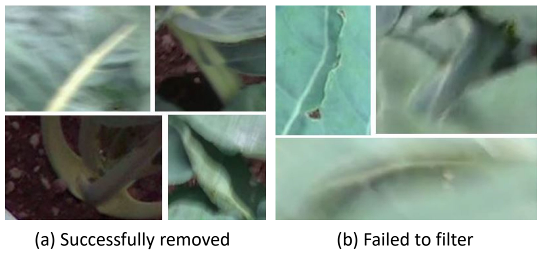

Figure 6. False positive cases predicted by YOLO network: Cases shown in (a) can be removed by HOG-SVM, while cases in (b) cannot.

normalizing the image size to $W \times W$ pixels. W is 80 in our experiment. All candidates that have high confidence values and have passed Θ_{SVM} are then sent to DeepSort [21]: $\Theta_{\text{DS}} : (I, \{\mathbf{b}_j\}) \rightarrow \{\eta_j\}, (j = 1, ..., \hat{n})$, where $\hat{n}$ is the number of detected and filtered objects' candidates, and η is the tracking id.

3.3 Spraying system

In our system, the robot arm's default position is set to face the robot's right side, and the end effector is oriented downward from a higher perspective. Given constraints including robot manipulator size, pump power, and depth camera range, we defined a spraying distance range of 25-55 cm with a circular spray area of approximately 30 cm in diameter. The distance from the spray to the target is obtained by the depth image taken by the RGB-D camera. Then a robot arm controller is utilized with tracking ID to move the end-effector to achieve a predefined spraying position. Furthermore, we have demonstrated the potential of robot arm manipulation in achieving low perspective positioning, which enables the identification of worms hidden under leaves.

4 Experiment

4.1 System details

Our platform utilizes a Unitree A1 robot as the main base. The spraying modules are built on a 6-DoF myCobot 280 M5stack robot arm, equipped with a RealSense L515 camera and a nozzle connected to a hose

Table 1. The number of detected worm's IDs under different configurations

Method	Conditions	Worms	Total	False tracked ↓	Duplicated ↓
Yolo + Deepsort	Imitation worms, sunny	14	101	46	41
Yolo + HOG-SVM + Deepsort			39	**5**	**20**
Yolo + Deepsort	Imitation worms, cloudy	14	237	142	81
Yolo + HOG-SVM + Deepsort			72	**24**	**34**
Yolo + Deepsort	Real worms, sunny	5	61	51	5
Yolo + HOG-SVM + Deepsort			28	**21**	**2**

and a 12V water pump mounted on the robot's front body. The camera is used to detect worms, while a 12V powered submersible pump inside a 280ml water container is used for spraying. Pump power is controlled by the digital GPIO of Raspberry Pi.

4.2 Dataset and training

To train our bounding box object detection model, we manually labeled images using LabelImg. The images of the pest-infested broccoli field were captured using a conventional camera with a resolution of 4032 $\times$ 3024 pixels. It should be noted that the majority of the worms in the frames were approximately 7% of the full image size, thus we divided the raw images into 12 tiles with a resolution of 1008 $\times$ 1008 pixels to address this issue. A total of 362 green worms were labeled in 4800 image samples, as illustrated in Fig. 3. The worm detection model was trained using a dataset split of 8:2 train-test ratio, with default values for Θ_{YOLO} training hyperparameters, including a batch size of 16 and a learning rate of 0.01. The training was conducted over 50 epochs on RTX3090. Our experiment results demonstrate that the dataset size is adequate for our model to achieve reasonable accuracy.

To address the limited accessibility of real broccoli fields, the HOG-SVM method's development, data collection, and testing were conducted on imitation broccoli fields that included broccoli heads, various leaf imitations, and plastic worms. We sampled 700 images from Θ_{YOLO} positive outputs with a balanced worm / no-worm ratio for training and 318 images for testing. The extracted HOG features from the Θ_{YOLO} results are presented in Fig. 4. Our experiments demonstrate that despite training the Θ_{SVM} using imitation models, it performs well in natural environments.

4.3 Experimental results

Our platform was tested in real broccoli fields. Due to the limited availability of real worms, we initially employed imitation worms in various weather conditions before applying our system to real worms. Figure 5 depicts our system operating in the broccoli fields and identifying cabbage worms in different orientations. In this experiment, robots were positioned on the side of broccoli crops with worms located randomly. Six repetitions were performed for each configuration with different weather conditions.

Table 1 presents the performance of our tracking method compared to other methods. The False Tracked column indicates the False Positive tracking IDs, and the Duplicate ID column displays the same detected worms being tracked with multiple IDs. Our method reduced false tracking by 89.13% and 83.09% under sunny and cloudy weather, respectively. The robot effectively maneuvered the arm and sprayed the worm-infested area in 13 out of the 14 target areas, with a quick transition time of 3 seconds per spray.

Fig. 6 provides sample cases of successful and failed to filter results of our proposed method. Our method filtered stalks and midribs successfully while failing to filter worm-like contour holes and blurred leaf veins. Failure cases may occur due to severe motion blur combined with a similar color of the worm-like contour of leaf veins and holes.

5 Conclusion

This study presents a quadruped robot platform for selective pesticide spraying on broccoli fields. Utilizing a Unitree A1 robot as the main base with integrating spraying modules, the system demonstrates high accuracy in worm detection with low false tracking and duplicate rates. Moreover, our proposed YOLO+HOG-SVM+DeepSort method for false positive reduction significantly reduces the occurrence of false tracking and duplicate IDs in worm detection. However, variations in illumination conditions can impact the system's performance, which might be attributed to unbalanced training data collection.

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References

[1] Boaz Arad, Jos Balendonck, Ruud Barth, Ohad Ben-Shahar, Yael Edan, Thomas Hellström, Jochen Hemming, Polina Kurtser, Ola Ringdahl, Toon Tielen, et al. Development of a sweet pepper harvesting robot. *Journal of Field Robotics*, 37(6):1027–1039, 2020.

[2] Owen Bawden, Jason Kulk, Ray Russell, Chris McCool, Andrew English, Feras Dayoub, Chris Lehnert, and Tristan Perez. Robot for weed species plant-specific management. *Journal of Field Robotics*, 34(6):1179–1199, 2017.

[3] Priyaranjan Biswal and Prases K. Mohanty. Development of quadruped walking robots: A review. *Ain Shams Engineering Journal*, 12(2):2017–2031, 2021.

[4] Karlos Espinoza, Diego L Valera, José A Torres, Alejandro López, and Francisco D Molina-Aiz. Combination of image processing and artificial neural networks as a novel approach for the identification of bemisia tabaci and frankliniella occidentalis on sticky traps in greenhouse agriculture. *Computers and Electronics in Agriculture*, 127:495–505, 2016.

[5] Bruno S Faiçal, Heitor Freitas, Pedro H Gomes, Leandro Y Mano, Gustavo Pessin, André CPLF de Carvalho, Bhaskar Krishnamachari, and Jó Ueyama. An adaptive approach for uav-based pesticide spraying in dynamic environments. *Computers and Electronics in Agriculture*, 138:210–223, 2017.

[6] Hans Johr. Where are the future farmers to grow our food? *International Food and Agribusiness Management Review*, 15(1030-2016-82830):9–11, 2012.

[7] S Kanase, S Patwegar, P Patil, A Pore, and Y Kadam. Agriculture drone sprayer. *International Journal of Recent Trends in Engineering & Research*, 4(3):181–185, 2018.

[8] Thenmozhi Kasinathan, Dakshayani Singaraju, and Srinivasulu Reddy Uyyala. Insect classification and detection in field crops using modern machine learning techniques. *Information Processing in Agriculture*, 8(3):446–457, 2021.

[9] Neha Kauser, Shabreen Banu, and T Yuvaraja. Iot based agricultural application using robot—agrobot. *Journal of Computational and Theoretical Nanoscience*, 15(6-7):2137–2139, 2018.

[10] Florian Johannes Knoll, Tim Holtorf, and Stephan Hussmann. Investigation of different sensor systems to classify plant and weed in organic farming applications. In *2016 SAI Computing Conference (SAI)*, pages 343–348. IEEE, 2016.

[11] Johnny L Miranda, Bobby D Gerardo, and Bartolome T Tanguilig III. Pest detection and extraction using image processing techniques. *International Journal of Computer and Communication Engineering*, 3(3):189, 2014.

[12] Roberto Oberti, Massimo Marchi, Paolo Tirelli, Aldo Calcante, Marcello Iriti, and Alberto N Borghese. Automatic detection of powdery mildew on grapevine leaves by image analysis: Optimal view-angle range to increase the sensitivity. *Computers and Electronics in Agriculture*, 104:1–8, 2014.

[13] Roberto Oberti, Massimo Marchi, Paolo Tirelli, Aldo Calcante, Marcello Iriti, Emanuele Tona, Marko Hočevar, Joerg Baur, Julian Pfaff, Christoph Schütz, et al. Selective spraying of grapevines for disease control using a modular agricultural robot. *Biosystems engineering*, 146:203–215, 2016.

[14] Yuki Onishi, Takeshi Yoshida, Hiroki Kurita, Takanori Fukao, Hiromu Arihara, and Ayako Iwai. An automated fruit harvesting robot by using deep learning. *Robomech Journal*, 6(1):1–8, 2019.

[15] Ege Ozgul and Ugur Celik. Design and implementation of semi-autonomous anti-pesticide spraying and insect repellent mobile robot for agricultural applications. In *2018 5th International Conference on Electrical and Electronic Engineering (ICEEE)*, pages 233–237. IEEE, 2018.

[16] Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi. You only look once: Unified, real-time object detection. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 779–788, 2016.

[17] Arno Ruckelshausen, Peter Biber, Michael Dorna, Holger Gremmes, Ralph Klose, Andreas Linz, Florian Rahe, Rainer Resch, Marius Thiel, Dieter Trautz, et al. Bonirob–an autonomous field robot platform for individual plant phenotyping. *Precision agriculture*, 9(841):1, 2009.

[18] Christian Scholz, Maik Kohlbrecher, and Arno Ruckelshausen. Camera-based selective weed control application module ("precision spraying app") for the autonomous field robot platform bonirob. In *International Conference of Agricultural Engineering, Zurich*, 2014.

[19] Christian Scholz, Kim Moeller, Arno Ruckelshausen, Stefan Hinck, and Matthias Göttinger. Automatic soil penetrometer measurements and gis based documentation with the autonomous field robot platform bonirob. In *12th International Conference of Precision Agriculture*, 2014.

[20] Jiangning Wang, Congtian Lin, Liqiang Ji, and Aiping Liang. A new automatic identification system of insect images at the order level. *Knowledge-Based Systems*, 33:102–110, 2012.

[21] Nicolai Wojke, Alex Bewley, and Dietrich Paulus. Simple online and realtime tracking with a deep association metric. In *2017 IEEE international conference on image processing (ICIP)*, pages 3645–3649. IEEE, 2017.

[22] Xiaolong Wu, Stéphanie Aravecchia, and Cédric Pradalier. Design and implementation of computer vision based in-row weeding system. In *2019 International Conference on Robotics and Automation (ICRA)*, pages 4218–4224. IEEE, 2019.

[23] Chengjun Xie, Rujing Wang, Jie Zhang, Peng Chen, Wei Dong, Rui Li, Tianjiao Chen, and Hongbo Chen. Multi-level learning features for automatic classifica-

tion of field crop pests. *Computers and Electronics in Agriculture*, 152:233–241, 2018.

[24] Yongjia Yu, Zengpeng Sun, Xiaoguang Zhao, Jiang Bian, and Xiaolong Hui. Design and implementation of an automatic peach-harvesting robot system. In *2018 Tenth International Conference on Advanced Computational Intelligence (ICACI)*, pages 700–705. IEEE, 2018.