Automated Weeding Systems for Weed Detection and Removal in Garlic / Ginger Fields

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***Abstract*—The global agriculture industry has faced various problems, such as rapid population growth and climate change. Among several countries, Japan has a declining agricultural workforce. To solve this problem, the Japanese government aims to realize “Smart agriculture” that applies information and communication technology, artificial intelligence, and robotics. Smart agriculture requires the development of robot technology to perform weeding and other labor-intensive agricultural tasks. Robotic weeding consists of an object detection method using machine learning to classify weeds and crops and an autonomous weeding system using robot hands and lasers. However, the approach used for these methods changes depending on the crop growth. The weeding system must consider the combination according to crop growth. This study addresses weed detection and autonomous weeding in crop-weed mixed ridges, such as garlic and ginger fields. We first develop a weed detection method using Mask R-CNN, which can detect individual weeds by instance segmentation from color images captured by an RGB-D camera. The proposed system can obtain weed coordinates in physical space based on the detected weed region and the depth image captured by the camera. Subsequently, we propose an approach to guide the weeding manipulator toward the detected weed coordinates. This paper integrates weed detection and autonomous weeding through these two proposed methods. We evaluate the performance of the Mask R-CNN trained on images taken in an actual field and demonstrate that the proposed autonomous weeding system works on a reproduced ridge with artificial weeds similar to garlic and weed leaves.**

***Keywords*—Weed detection; weeding; mask R-CNN; agriculture robot**

I. Introduction

According to the 2022 report on new farm employment by the Ministry of Agriculture, Forestry, and Fisheries of Japan [1], not only has the number of new farmers been declining for the past few years, but also the ratio of people aged 49 or younger has been declining among new farmers, reflecting the shortage of workers in the agricultural sector as a whole. In addition, the world’s population is expected to reach approximately 9.1 billion by the end of 2050, and food demand is expected to increase by 70% from the current level. India is expected to be the most populous country by 2050, but even today it is already unable to meet its domestic food production needs [2]. Against this background, there is a growing interest in the widespread adoption of smart agriculture, which uses artificial intelligence, internet of things, and robots, with particular attention focused on the use of autonomous agricultural robots to replace human agricultural workers [3].

In agriculture, weeding is important in maintaining the growth and quality of crop plants. Normally, the crop plants grown in farmlands compete with plants that naturally propagate in the same area (hereafter referred to as “weeds”). To safely prioritize the growth of crop plants over weeds, it is necessary to carry out multiple weeding operations to remove the weeds before harvest [4]. However, as weeding is physically demanding, various researches on automated weeding using robots is being pursued. Ghazali et al. proposed the machine vision system for automatic weeding strategy [5]. They compared several image processing methods, and studied suitable one for weed detection. Mary et al. proposed a weeding robot for crop and weed discrimination using Convolution neural network (CNN) [6]. Ya et al. developed a weeding robot and its path planning method [7]. Yasuda et al. proposed a sweeping weeding method using brush rollers [8]. Sweeping weeding is effective when crops are planted in regular rows. However, when crops are planted irregularly, the sweeping method may damage the crops, weeding by manipulators is effective [6]. This paper studies an automated weeding system using manipulators for irregularly planted crops in the field. Various automated-weeding methods exist, but the primary tasks in weeding include: (1) the detection of the weeds to be removed and (2) guiding the weeding mechanism to those weeds [9]. As weeds and weeding periods differ depending on several factors, such as the type of crop plant, cultivation method, and environmental conditions, general-purpose weed detection is difficult [10].

Many existing studies on smart agriculture that focused on differentiating crop plants and weeds have confirmed the usefulness of convolutional neural networks (CNNs) and you only look once (YOLO) [11] [12] [13]. Narayana et al. used YOLOv7, which is capable of high-speed object detection, to detect and classify weeds into multiple weed types based on their shapes using images of weeds for training [14]. However, if the weeds and crop plants are similar in appearance, there is a possibility that crop plants may be mistakenly detected as weeds. Elnemr [15] developed a weed-detection system based on a deep convolutional neural network (DCNN) using a dataset comprising weeds in the early stage of germination. This study successfully detected weeds in the early stages of germination, demonstrating that they could be weeded before they inhibit crop plant growth.

The environment in which both weeds and crop plants grow is called a “ridge,” which is a row of earth raised into a mound for planting. For the weeding task, it is important to construct and use a dataset with images of both crop plants and weeds so that crop plants can be excluded from weeding based on their features. Most studies on weed detection for weeding focus on evaluating the detection accuracy and ignore the actual application to the task of weeding [16] [17].

With the goal of automating the weeding process, this study proposes a weed-detection and removal method that uses images obtained from a real environment for detection and robot arms to remove the detected weeds; the real environments is an open outdoor field where garlic and ginger leaves are cultivated. We propose a system that not only evaluates the detection accuracy based on a training dataset, but also investigates the impact of the weeding task and removal control after the weeds are detected. By proposing an actual weeding system, the study contributes to the construction of automated systems for weeding tasks.

The remainder of this paper is organized as follows. In Section II, we construct a dataset necessary for weeding tasks and propose a weed-detection method using the dataset. We also propose a method for weed removal using this weed-detection method. In Section III, we report on experiments to verify the function of our proposed weeding system. In Section IV, we summarize this study and discuss the future prospects.

II. Construction of the Weeding System

A. Prerequisites

This study targeted an open cultivation field, as depicted in Fig. 1, where crop plants are not lined up in rows. In such fields, the crop plants such as garlic and ginger having long leaves and stems grow vertically upward out of the ridge. If weeds grow among the crop plants, they will negatively impact the growth of the crop plants. Therefore, weeding must be performed multiple times as the crop grows. When the crop grows taller than the weeds, the influence of weeds on the growth of the crop reduces; thus, the weeding rate of the entire field can be lower than 100%.

Fig. 1. Assumed environment.

Previous studies have proposed a mowing robot for weed removal and a weeding robot that tows a rake-like tool through crop fields [18] [19]. The weeding robot in the current study detects the individual plants to be weeded and then guides the manipulator or a similar tool to the weeding point to avoid damage to the crop plants. To achieve this, the robot uses a system that moves along the ridge, captures the conditions of the ridge underneath the robot using a camera, and then uses robot arms to remove the weeds, as illustrated in Fig. 2.

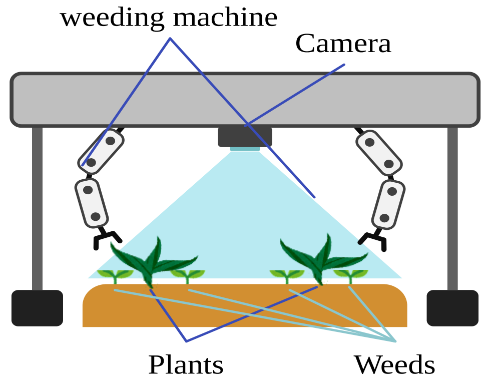


Fig. 2. Overview of weeding robot.

B. Proposed Method

The approach in this study is as follows. An RGB-D camera first detects weeds based on color images and calculates their spatial coordinates based on depth images. Thereafter, the robot arms are guided to the detected weeds.

In the field where our target crop plants are grown, the weeds growing among the crop plants include plants with a variety of leaf shapes and growth patterns, including henbit deadnettle (Lamium amplexicaule) and annual meadow-grass (Poa annua). To detect individual weeds, we used Mask R-CNN with instance segmentation, a machine learning algorithm [20] that allows the detection of individual weeds in plant clusters. The VGG (Visual Geometry Group) Image Annotator was used to create the training data. The machine learning model was trained using 500 images taken from a real field [21].

Next, we calculated the physical space coordinates—the target coordinates for the weeding mechanism—based on the weed-detection images. As the center of gravity with respect to the weed-detection area is as close as possible to the root of the weed, it is therefore necessary to guide the weeding mechanism to this spot [22]. Three-dimensional spatial coordinates were then calculated for these camera coordinates based on the depth image and camera parameters.

Finally, after converting the target coordinates from the coordinate system on the RGB-D camera described above to the coordinate system of the manipulator, the position of the end effector that grips the weed was guided to the coordinates of the root of the weed as follows:

1) The robot arm was moved so that the horizontal plane coordinates of the end effector aligned with the target coordinates.

2) Based on the depth information obtained by the RGB-D camera, the end effector was lowered to the weed surface.

3) To remove the weed, it was grasped by the end effector and pulled up.

4) The manipulator was moved to its home position and the gripped weed was released.

III. VERIFICATION OF THE WEEDING SYSTEM FUNCTIONS

A. *Evaluation of Detection Accuracy by Annotation Shape*

The training parameters are shown in Table I. The PC used for training was configured as shown in Table II, and the training was performed using detectron2 provided by META. Training time required to build the machine learning model using 500 images on this PC was approximately fifteen minutes. Object detection using Mask R-CNN depends on the accuracy with which the annotation task is performed. Therefore, we trained the detection model on two types of weed datasets: rectangular (in which the weeds were annotated as rectangles) and polygonal (in which the weeds were annotated as polygons), and their detection accuracies were compared. As target-coordinate detection for weed removal is important in this study, we counted the number of annotation labels in which the center of gravity of the detected weed is contained in the weed area in 20 test images. The results are shown in Table III. Fig. 3 shows examples of weed detection using each annotation shape, and Fig. 4 shows examples of the weed centers of gravity.

TABLE I. THE TRAINING PARAMETERS

Batch size	128
Iterations	1000
Learning Rate	0.0003

TABLE II. THE PC CONFIGURATION USED FOR TRAINING

CPU	Intel Core i5
GPU	Geforce RTX3050Ti
OS	Ubuntu 18.04
Training Time	15 min / 500 images

TABLE III. COMPARISON OF RESULTS BY ANNOTATION SHAPE

Annotation	Total weeds	Total detections	Total off the top of weeds	Accuracy
Rectangle	214	199	8	0.851
Polygon	214	278	5	0.852

(a) Rectangle result.

(b) Polygon result.

Fig. 3. Comparison of results by annotation method.

(a) Rectangle.

(b) Polygon.

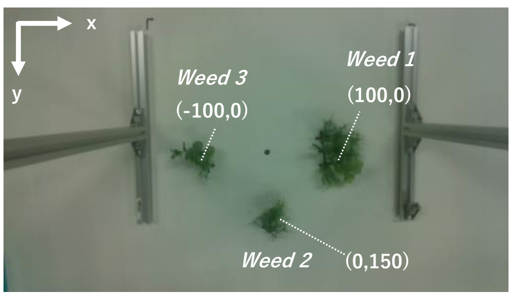
Fig. 4. Results of each weeding-point drawing.

Fig. 4 shows that the center of gravity is positioned on the top of the weed for both the rectangle and polygon annotation shapes. However, when we compared the results on the same 50 test images, we found that the total number of detections was higher in the system trained on polygonal annotations. The fact that the training results were more accurate for polygon annotation suggests that the polygonal annotation was more effective for training the weed detector of the weeding robot.

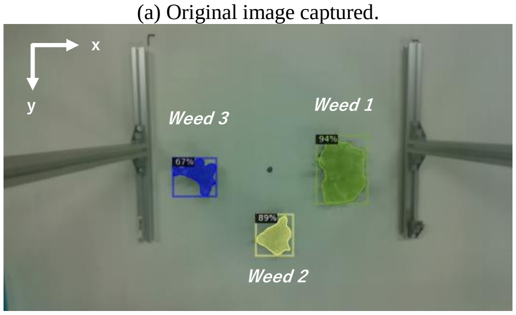
B. Experiment to Calculate Spatial Coordinates for Weeding

The accuracy of spatial coordinates is important to properly guide the weeding mechanism to the target weeds. Therefore, in an experiment, we placed artificial flowers on a sheet of imitation Japanese vellum to confirm whether the coordinates obtained using our weed-detection method and coordinate transformation were appropriate. The RGB-D camera used in this experiment was the Intel RealSense D435i.

In the experiment, we arranged the artificial flowers as “weeds” on a square paper as shown in Fig. 5 such that three “weeds” of different sizes were in the field of view of the camera, and then verified the accuracy of the two-dimensional coordinates after object detection by comparing them with actual measured values. The weed sizes and labels from right to left are—large (Weed 1), medium (Weed 2), and small (Weed 3).



(a) Original image captured.



(b) Masked image.

Fig. 5. Results of weed-location detection experiment.

Table IV shows the coordinates where the weeds were placed, Table V shows the calculated coordinates, and Table VI shows the difference between the results in Table IV and Table V. It was confirmed that there was a maximum difference of 30.0 mm in the x-direction. Weed 3, which was the smallest, had a difference of 8.30 mm, while Weed 1 and Weed 2 had a difference of 30.0 mm. This is probably because as the size of the detection target increases, the center of gravity of the generated mask region moves away from the center of the weed. However, even with a maximum error of 30.0 mm, the weeding point was within the weed-detection area, thus the results of this experiment were considered acceptable. In future, we plan to confirm the effectiveness of our approach when performing manipulation control in actual fields.

TABLE IV. THEORETICAL VALUES OF TWO-DIMENSIONAL COORDINATES

	Actual Arrangement	
Index	**X [mm]**	**Y [mm]**
Weed 1	100	0
Weed 2	0	-100
Weed 3	-100	0

TABLE V. MEASURED VALUES OF TWO-DIMENSIONAL COORDINATES

	Measurements	
Index	**X [mm]**	**Y [mm]**
Weed 1	130	1.48
Weed 2	30.0	-108.2
Weed 3	-91.7	6.98

C. Manipulation Control Experiment

Further, we confirmed the ability of the system to guide the robot arms to the weeds based on the proposed method. In this experiment, we conducted an evaluation in an artificial environment in which soil was placed in a shallow tray, and artificial flowers were placed on top of the soil as weeds. The manipulation control was performed using the spatial coordinates of the weeds obtained by the weed detection and coordinate transformation evaluated above. The manipulator used in this experiment was a Dobot Magician, a tabletop 4-axis manipulator manufactured by Dobot Robotics. Fig. 6 shows the experimental setup. The control flow implemented for the manipulation is shown in Fig. 7.

TABLE VI. ERROR BETWEEN THEORETICAL AND MEASURED VALUES

	Error	
Index	**X [mm]**	**Y [mm]**
Weed 1	30.0	-1.48
Weed 2	30.0	-8.20
Weed 3	8.30	6.98

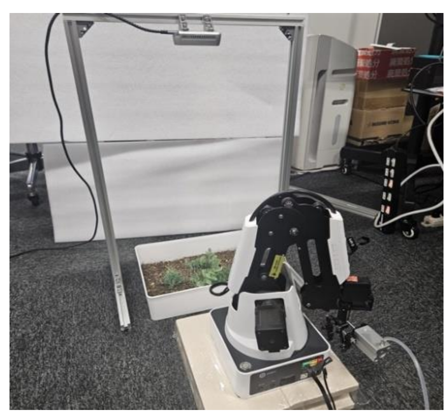


Fig. 6. Experimental environment.

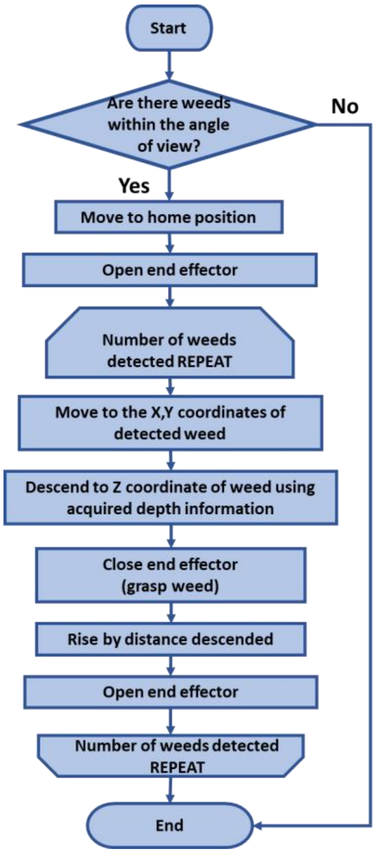
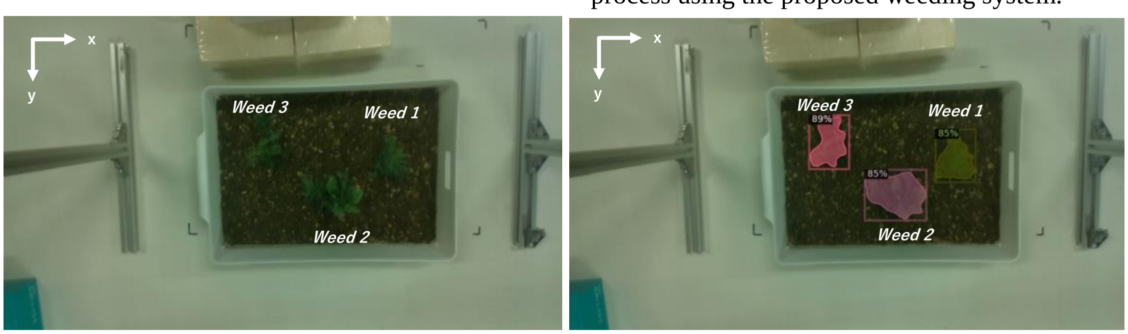


Fig. 7. Flowchart of manipulation control.

We calculated the three-dimensional coordinates as described in the previous section. The calculated three-dimensional coordinates are shown in Table VII.

We assigned the weed numbers, starting with Weed 1 in the lower right corner. An example of the original captured image is shown in Fig. 8(a) and the same image with the corresponding masked areas that were generated as shown in Fig. 8(b). The manipulation control was applied to the three coordinates shown in Table VII, and all the three weeds were successfully grasped. Fig. 9 shows an example of the weeding process using the proposed weeding system.



(a) Captured image. (b) Masked image.

Fig. 8. Experimental results in a simple field

TABLE VII. THREE-DIMENSIONAL COORDINATES

	Actual Arrangement		
Index	**X [mm]**	**Y [mm]**	**Z [mm]**
Weed 1	-24.8	-49.2	562.0
Weed 2	69.9	22.8	564.9
Weed 3	151.8	24.1	558.0

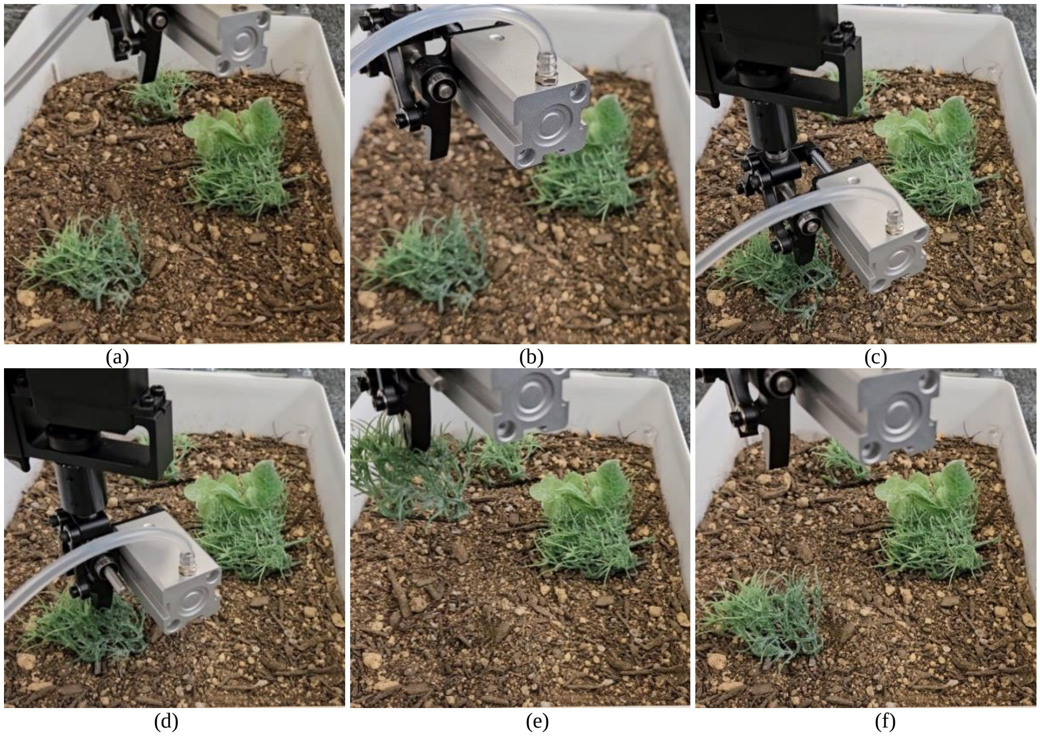


Fig. 9. Weeding Scene. (a) Initially, the robot arm is in the home position. (b) The end-effector is moved by the robot arm so that its horizontal plane coordinates match the target coordinates. (c) Based on depth information, the end-effector is lowered to the surface of the weed. (d) The end-effector grasps the weed. (e) The robot arm moves and pulls the weed out with the end-effector. (f) After releasing the grasped weed, the robot arm moves to the home position.

D. Discussion

From the above functional verification, the following results were obtained for the weeding system functions.

- The polygonal annotation was more effective than rectangular annotation for training the weed detector of the weeding robot.
- The center-of-gravity position was within an acceptable range for the maximum error in the weeding position calculation.
- The manipulation control was applied to the calculated three-dimensional coordinates of weeding points, and the weeds were successfully grasped.

Fig. 10. Example of weeds that are difficult to detect center-of-gravity position.

By setting the manipulation control point at the center of gravity of the segmentation mask, rather than at the center of the bounty box, the weeds could be approached correctly in many cases. However, depending on the shape of the weeds, as shown in Fig. 10, weeding could not be performed correctly. We believe that the construction of a network to predict weed roots after weed detection is one of an important issue to be addressed in the future.

IV. Conclusion

We believe that smart agriculture is an effective way to address the labor challenges facing the agricultural sector of Japan. Focusing on the weeding task, which is one of the most burdensome agricultural tasks because it must be done multiple times before harvesting, we investigated weed detection and removal to implement an automatic weeding robot.

To realize the automatic weeding robot, we built a series of functions—including weed detection using Mask R-CNN, calculation of the three-dimensional coordinates of detected weeds, and manipulation control to the detected coordinates—and confirmed the effectiveness of these functions through operational verification.

In future work, we plan to experimentally verify these functions in an actual field. In addition, as it is necessary to distinguish between crop plants and weeds more accurately in actual operation, we also plan to study ways to improve detection accuracy, for example, by enlarging the dataset and investigating other training techniques. Moreover, since not only a single robot but also a multi-robot system with multiple robots is effective for actual operation in the field [23], a multi-robot system version of the system in this paper will also be considered.

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