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Development of Agriculture Robot for Plant Detection and Fertilizer Dispense

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Abstract— **With the growing world population, limited agriculture resources and reduced number of people working in agriculture sector, the need for intelligent autonomous robots is increasing. Agriculture robots must perform a wide range of operations like spraying pesticides, dispense fertilizers, remove weeds. In this paper, we explain in detail an agriculture robot developed in Assistive Robotics Laboratory, Hosei University. It consists of three subsystems: 1) The wheel-type actuated system; 2) A parallel link arm and 3) Fertilizer system. The robot utilizes the visual information and the Convolution Neural Networks to recognize the target plants. To evaluate the performance of developed robot, we performed experiments for spinach recognition, fertilizer dispenser and robot spraying.**

I. Introduction

Spraying pesticides in agriculture fields takes time, effort, and physical strength. It is a hard work and requires skills to select the type of pesticide. According to the "White Paper on Aging Society for the Second Year of Reiwa" as of October 1, 2019, the population aged 65 and over was 28.4% of the total population [1]. In Japan, the number of people aged over 65 was less than 5% of the total population in 1950 and 14% in 1994 and elderly people percentage is increasing every year. As a result, the working-age population is highly effected. In Japan, the number of agricultural workers continues to decrease year by year. Recently, it has decreased by about 100,000 every year. Half of people working in agricultural are over 70 years significantly older than other industries. Fig 1 shows area of cultivated land per farmer is increasing year by year especially in Hokkaido region.

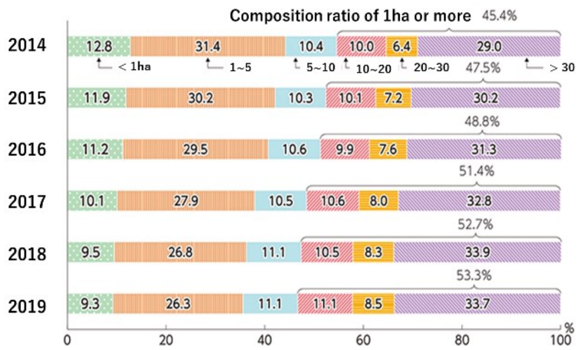


Fig. 1. Changes in the area of cultivated land managed per farmer.

Based on the above consideration the smart agriculture aims to further improve production efficiency and add value to agricultural products by linking conventional agricultural technology and robot technology. For example, with smart agriculture, the input of chemical fertilizers and spraying of pesticides for quality improvement can be optimally adjusted according to the conditions of soil and crops. Smart agriculture utilizes new agricultural methods such as precision agriculture and Agri Informatics agriculture, and general-purpose software and hardware technologies that are common to other fields such as networks, information terminals, cloud computing, remote sensing, and robots. In addition, the goals of smart agriculture are (1) realization of ultra-labor-saving and large-scale production; (2) maximization of crop capacity; (3) release from hard work and dangerous work; and (4) realization of easy to work agriculture environment. On the other hand, the current issues are (1) high initial cost; (2) insufficient infrastructure development; and (3) insufficient learning opportunities for smart agricultural.

As part of the smart agriculture projects several robots designed to operate in agriculture environments are developed. For example, Durmus et al. (2015) ([1]) proposed a multi-purpose robot called Agrobot. The robot interacts with the farmers wirelessly. However, the robot could not operate autonomously. A greenhouse partner robot system was developed by Kashiwazaki et al. (2010) ([2]) The authors utilized the sensors to track the guidance lines. However, the robot operates only inside the greenhouse and not in open agriculture fields. Amer et al. (2015) ([3]) proposed a multi-direction moving robot called Agribot is developed to perform several agriculture tasks. However, due to WiFi connection can operate in small areas. Gonzalez-de-Santos et al. ([4]) designed, a robotic system for effective weed and pest control. A fleet of heterogeneous ground and aerial robots was developed to cover a large variety of agricultural situations. In addition, several vision-based agriculture robots have been proposed ([5], [6]).

In this paper, we propose an agriculture robot that navigates in the field recognizing and tracking the target plants. As the robot moves through the target plants, the robot recognizes the diseased plants and spray the appropriate pesticide. It is estimated that the total amount of pesticides used can be reduced to 1/20. In this paper, we have implemented the Faster RCNN for spinach and anthrax decease recognition. The robot implementation shows a good performance.

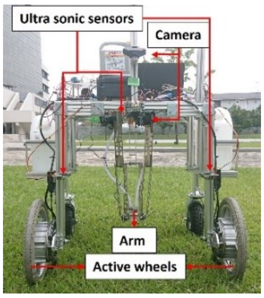
II. Developed Robot

In Human Assistive Robotics Lab., Hosei University, we have developed the agriculture robot shown in Fig 2. The robot is 720 (mm) in length and 830 (mm) in height. The width can be adjusted in the based on the agriculture environment and operation in the range 360mm to 790mm. The system consists of a control PC, a webcam. The robot motion is actuated by two AC motors (Yamaha Motor Electric Wheelchair R & D Kit) on the left and right front wheels. By using two USB cameras, you can grasp the direction of travel and the state of the crop respectively. To increase the durability of the main body, the robot frame is aluminum A6N01SS-T5. Therefore, the load capacity is about 60 kg. The tires are 40 (cm) for the front wheels and 26 (cm) for the rear wheels. The maximum moving speed is about .4.2km / h.

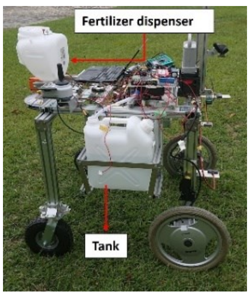
A parallel link arm (Fig 3) moves in 3D space inside the robot space to move the spraying nozzle in the target position. Servo motors are used to move the robot arm and are attached to the tops of each of the three arms. Since the servo motors generate heat during use, a fan is installed nearby. The data flow of agriculture robot is shown in Fig 4. The camera captured image is processed by the control PC. In the captured image the targets plants are recognized, and the command is sent to AC motors such as to follow the targets plants. In the addition, the diseased plants and their location are determined, and the appropriate command is sent to the servo motor positioning the nozzle above the diseased plant or healthy plant.

In the rear part of the robot is installed the fertilizer unit (Fig. 2(c)). The fertilizer is placed in a 8 Liter volume. The rotation of the spreading disc is related with the diameter of the spreading fertilizer. It varies from 0.3m to 6m in diameter. A DC motor controls the rotating speed of the spreading disc.

(a) Front side view



(b) Front view



(c) Side view

Fig. 2. Developed robot.

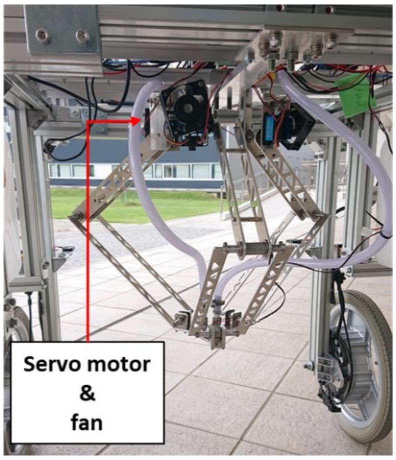


Fig. 3. Parallel link robot arm.

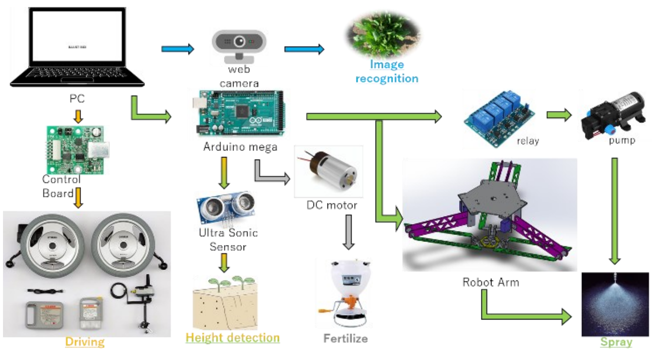


Fig. 4. Robot data flow.

III. Deep Learning for Spinach and Anthrax Disease Recognition

Deep Neural Network (DNN) is a multi-layered algorithm modeled on human and animal brain neural circuits designed to recognize patterns([7], [8], [9]). DNN automatically extracts features from training data. Especially in image recognition technology, it is common to use a Convolutional Neural Network (CNN), and Faster R-CNN. Fig 5(a) shows the structure of Faster R-CNN used in this work. The learning is performed in two steps: Step 1: Learn whether the contents of a certain short diameter are an object / background; Step 2: Learn what is specifically reflected in the location detected in Step 1; Faster R-CNN uses a CNN structure called Region Proposal Networks (RPN) for object recognition. RPN is a machine learning model that can detect where an object appears in a certain image. RPN requires teacher data for training. The procedure for creating teacher data is shown below: Step 1: Output the feature map from the input image; Step 2: Set Anchor boxes for the feature map; Step 3: Create RPN teacher data while comparing Anchor boxes and Ground Truth information.

The feature map is the output layer when a certain input is passed to the last convolution layer using a trained model such as VGG16. The design of the VGG-16 architecture is described in detail by Simonyan et. al. [10]. The feature map shown in Fig 5(b) points to the $14 \times 14 \times 512$ layer just before the last pooling layer. When VGG16 is selected as the trained model, it is pooled four times, so the feature map is 512-

dimensional data with 1/16 the height and width of the original image. RPN is not used in the layers after the feature map of $7 \times 7 \times 512$ or later is output. For example, if the input is $240 \times 240 \times 3$, the feature map will be $15 \times 15 \times 512$. 480x

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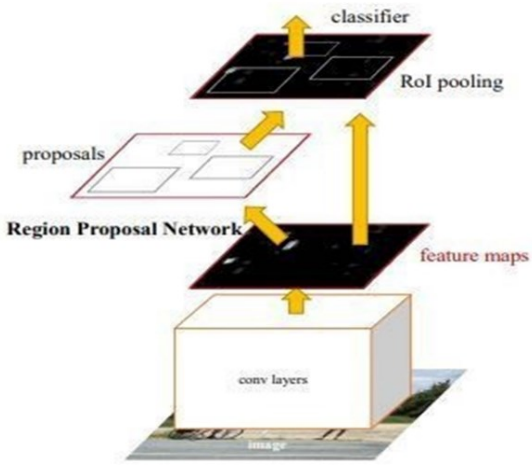
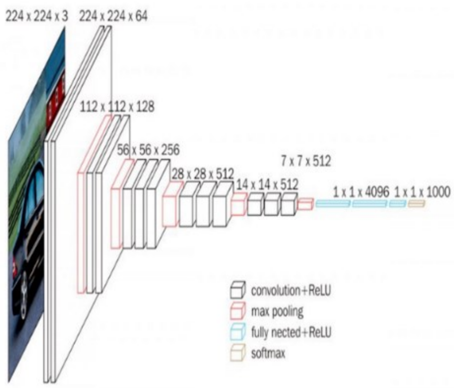
* VGG16 is a neural network created by the VGG team with 13 convolution layers + 3 fully connected layers-16 layers.

In this work, we tested the performance of two Faster RCNNs: a) Faster RCNN1 for only spinach plant recognition; b) Faster RCNN2 for simultaneously recognizing the spinach and anthrax recognition.

There are several types of spinach diseases, such as anthrax, wilt, and downy mildew. Anthrax is a decease caused by "mold" that occurs in all vegetables. Symptoms of anthrax are the appearance of circular spots with brown (gray white) green spots, the central part becoming lighter in color, and black particles. Symptoms may also appear on the stems and flowers. If anthrax is left untreated, the lesions on the leaves and stems will gradually grow and eventually die. Anthrax is likely to occur in poorly drained soil and in a humid environment. Wilt is a disease caused by "mold" like anthrax, affecting seedlings immediately after planting, which is called seedling wilt disease.



(a) Structure of implemented



(b) Feature map

Fig. 5. Structure of Faster R-CNN.

Symptoms of wilt disease often appear on the stems, and when infected during the seedling stage, the stems near the ground become stained with water and rot. When the disease develops after the strain has grown, symptoms appear throughout the strain, and the growth begins to decline rapidly, and the entire strain may wither during the day. If the wilt disease is left unattended, it will wither during the day and stop growing, and finally the strain will not recover its momentum and will die as if it were black and dry. Bacterial wilt is more likely to occur in poorly drained clay soils when it becomes humid. Finally, downy mildew is also a disease caused by "mold". Downy mildew is characterized by the development of pale or yellowish-white lesions and soot-like mold on the underside of the leaves. If downy mildew is left untreated, the initially scattered lesions will stick together and expand, and soot-like mold will grow on the back of the leaves. If left untreated, the central part of the lesion turns black and the weak strain dies. As conditions that are likely to cause the disease, it is likely to occur in poorly drained soil when daylighting and ventilation are poor.

IV. Experimental Results

A. Deep learning for spinach and anthrax recognition

The number of data used for training the Faster RCNN 1 is 300 pictures. The captured camera imagen is used as input of the Faster RCNN. In our experiments, the number of spinach plants in each picture varies. Fig 6 shows the spinach recognition results by Faster RCNN. In addition, we verified the performance of Faster R-CNN as the spinach grows. The results are shown in Table 1. Not surprisingly, the results show that the recognition rate increases when the training data and robot testing are performed in a short time lag.
Next, a Faster RCNN is trained to classify the anthrax and normal spinach. We created a dataset of pictures in which normal and diseased spinach are shown. Although we utilized printed anthrax leaves, the Faster RCNN 2 distinguished between normal and anthrax spinach. These results are shown in Fig 7.

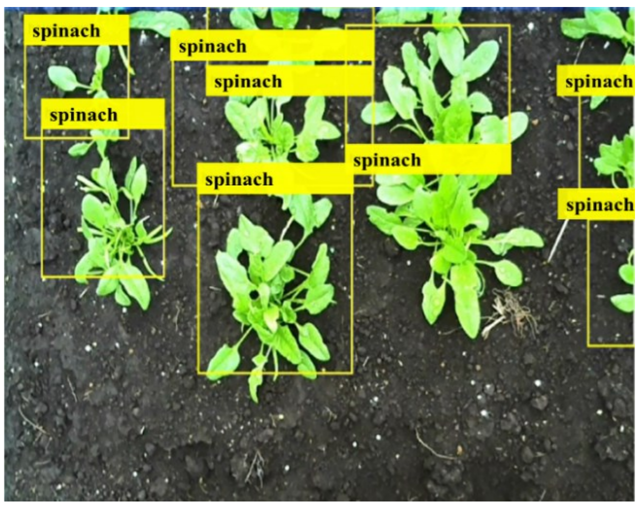


Fig. 6. Spinach correctly recognized by Faster R-CNN

TABLE I. THE RECOGNITION RATES FOR PICTURES TAKEN AFTER 2 DAYS, 1 WEEK, 2 WEEKS.ABLE TYPE STYLES

Time since data collection	*Matching score (%)*	*Recognition rate (%)*
2 weeks	70	5
	60	10
	50	20
1 week	70	30
	60	50
	50	70
2 days	70	85
	60	90
	50	95

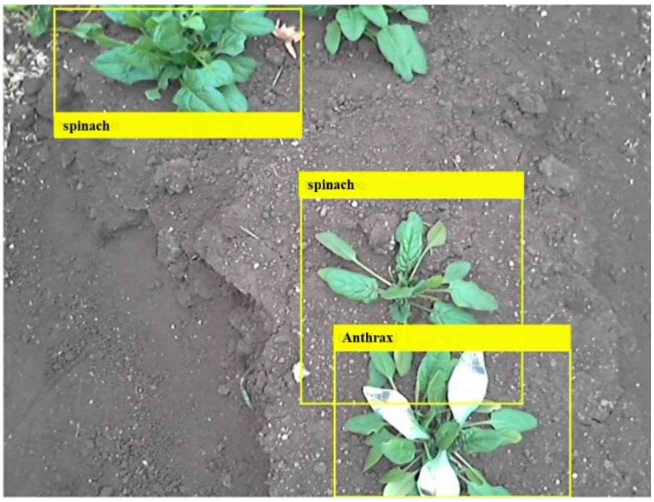


Fig. 7. Normal and anthrax spinach correctly recognized by Faster R-CNN 2

B. Robot arm motion using the vision system

In our implementation, detecting the spinach and anthrax is based on processing the image captured by the camera mounted in front of the robot. The image 480 x 640 pixels is processed in real time. When plant is recognized in the captured image, and it is surrounded by a green rectangle (Fig 6). Based on the center of the green rectangle, the target square is determined (red square in Fig 8). A1, A7, G1, G7 are not included because the robot arm can not reach these positions.

Next, to spray pesticides, we constructed a system that controls the robot arm according to the position of the target plant recognized in the captured image. The coordinates of the recognized target on the camera are converted to the target robot arm coordinates (x,y) in mm. The z coordinate is determined using ultrasonic sensors. Since the position of the coordinate system is at the top of the robot arm (z = 0 mm), the z-coordinate of the plant has negative value. From those coordinates, the input angle to each servo motor of the robot arm is calculated. To avoid robot arm collision with the plant an arbitrary offset in the a-coordinate is added to the

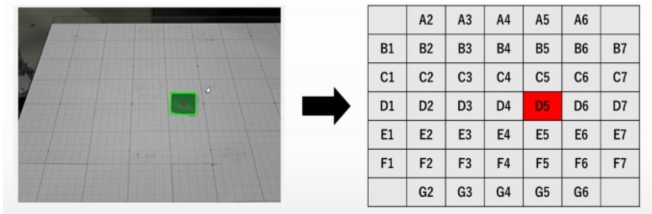


Fig. 8. Moving location of the robot arm

(a) Input (x,y,z)=(0,0,-350)

(b) Input (x,y,z)=(0,0,-500)

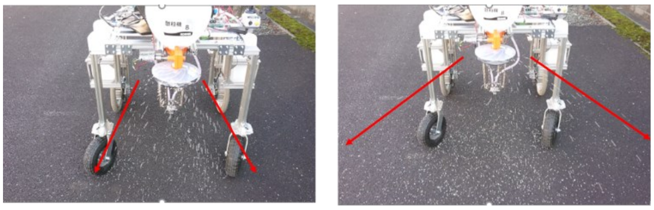
(c) Input (x,y,z)=(-100,0,-350)

Fig. 9. Comparison of spraying range of fertilizer machine

calculated value. Fig. 9 shows the experimental results where the robot arm must move in 3 different positions determined based on the robot sensors. The difference between the target and the robot arm locations are shown in Fig. 9.

C. Fertilizer dispenser and robot motion

The DC motor axis is cupled with the rotating disc to distribute the fertilizer. As the speed of the rotating disc increases, the distributed width of falling fertilizer also increases. Therefore, the user can set the width. In the control program we convert the desired width to the target PWM value send to the the DC motor. Fig. 10. shows the difference in the spreding range when PWM control is performed.



(a) 13 [rpm] (b) 36 [rpm]

Fig. 10. Comparison of distribution range of fertilizer unit

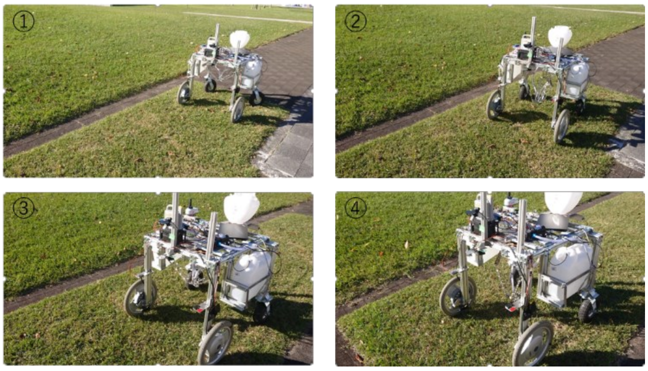


Fig. 11. Video captures of mobile platform and arm motions

Fig. 11. shows the integration of the mobile platform and the robot arm motions. The robot is moving with a speed of 0.3m/s. In specific locations the robot arm is actuated to move in the vertical directions.

V. Conclusion

In his paper, we presented an agriculture robot developed in our Laboratory. The robot is composed from 3 systems: the mobile platform; the robot arm for spraying pesticides; and the fertilizer dispenser. The robot was designed such that it can perform a wide range of operations in the agriculture fields. We presented the results for arm motion generation, spinach and anthrax recognition and the fertilizer dispenser. The results were promising. The robot arm reached the target location based on the captured camera image. The Faster RCNNs performed well for plant recognition. However, the performance of Faster RCNN in different environments must be evaluated. In addition, integrating all these systems for the robot multitask performance in the agriculture field is still a challenge that we are working on.

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