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Autonomous Drone-Based Pollination System using AI Classifier to Replace Bees for Greenhouse Tomato Cultivation

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ABSTRACT In greenhouse tomato cultivation, three primary methods of flower pollination exist: insect pollination, physical pollination by vibrating flowers, and artificial pollination using hormone-based chemicals. Insect pollination, the natural method, involves insects (e.g., honeybees) vibrating flowers to collect pollen and nectar. This paper proposes an alternate approach, using small drones to search and pollinate flowers in place of bees autonomously. We report field experiments conducted using these drone technologies. The drone must locate flowers ready for pollination. We developed an artificial intelligence (AI) image classification system (AI classifier) using machine learning to identify these flowers. Equipped with an AI classifier, the drone searches for flowers through autonomous flight and positioning technology. Upon identifying a suitable flower during its search, the drone makes contact to pollinate it. Integrating AI-based flower detection, autonomous flight control for flower search, and a pollination control device allows the drone to perform pollination. This study devises these technologies, implements them in a drone, and evaluates their effectiveness through a pollination experiment.

INDEX TERMS Autonomous drones, Greenhouse tomato cultivation, Pollination methods, pollination, AI image classification, Flower search, Pollination control device

I. INTRODUCTION

SMART agriculture is an innovative approach that integrates engineering techniques and chemical processes to optimize agricultural operations and growth. It aims to reduce labor, improve crop quality, and increase production [1]–[4]. The approach uses information and communication technology, the Internet of Things, and other information science technologies to gather data on temperature, humidity, sunlight hours, soil composition, and other factors for effective cultivation management. Furthermore, research on robots assisting in cultivation to save labor is underway. Robot-assisted cultivation technology has gained significant attention due to its potential applications in various areas, such as pesticide application for pest control [5], [6] and automated crop harvesting [7]–[10]. In [5], a fruit tree pest identification system using drones is proposed, where a drone takes pictures of pests, and after determining the location of the pests, their locations are used to plan a pesticide application route. In [8], an unmanned aircraft system called AgriQ is proposed, in which a drone equipped with a multispectral image processing system flies to the agricultural field to take multispectral images and calculate vegetation indices useful to farmers based on the images. In [9], drones have been experimented with applying fertilizers and pesticides to rice

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paddies and have been shown to improve the efficiency of agricultural activities considerably. As these studies show, robot-assisted cultivation technologies are expected to be very useful for efficient crop cultivation, but few studies have addressed robot-assisted pollination [6], [7], [10]. Automation of the pollination process by robots is an important technological challenge because no fruit is produced without pollination.

We developed an autonomous drone-based pollination system for tomato cultivation. Tomato cultivation has high demand, as tomatoes rank first in global crop production at 1.8 million tons [11]. Despite their popularity, tomatoes pose numerous cultivation challenges, one of which is pollination.

A. PROBLEM STATEMENT

Plant pollination involves the production of seeds and fruits after pollen from the stamen attaches to the pistils. Tomatoes are "self-pollinated," meaning pollination occurs by shaking either the same flower or plant. Numerous studies on pollination are underway [12]–[17]. Greenhouse tomato cultivation employs three pollination methods: natural pollination by insects, manual pollination using a vibrating device (e.g., an electronic toothbrush), as shown in Fig. 1, and artificial pollination using synthetic plant hormones. Insect pollination, a natural method, relies on insects such as honeybees and bumblebees, vibrating anthers of flowers to collect pollen, as shown in Fig. 1(a). However, insects can be difficult to maintain and manage, and their activity declines at high temperatures during summer, leading to lower pollination efficiency. Moreover, there are limitations to using commercial bumblebees in countries such as Japan and Australia due to ecological risks [16], [18]. Therefore, artificial pollination involving manual flower vibration devices has been employed, as shown in Fig. 1(b). In this method, workers visually classify flowers ready for pollination and shake them using vibrating devices, indicating high labor costs.

Another pollination method uses hormones and plant growth agents to promote fruit set and growth. Hormone treatment is useful since it does not require classifying flowers that can be pollinated, and pollination can be performed easily. Furthermore, inappropriate hormone use may cause chemical damage and lead to quality problems such as reduced fruit shape and taste [19], [20].

B. AIM OF PROPOSED SYSTEM

This paper proposes new pollination methods, as illustrated in Fig. 2. We developed a system to address the challenges above in various pollination methods. The proposed method employs small drones or service robots instead of bees or humans for pollination. The advantage of using drones instead of bees is their mobility. Tomatoes for fresh consumption are cultivated in greenhouses in a controlled environment to grow upwards, as shown in Fig. 3. Flowers bloom by clusters per shoot, step by step, and are sequentially fruiting. Therefore, the height of the flower changes step by step as it grows. The drone flight is suitable for pollination in a three-dimensional space, including height. Moreover, when using a ground-moving robot, it is necessary to build a greenhouse with fixed rails and a special structure that allows the robot to operate to overcome the unevenness of the ground. Therefore, drones that work flexibly are suitable for tomato pollination.

(a) Pollination by bumblebees

(b) Pollination by manual vibration

FIGURE 1. Conventional general pollination methods.

C. METHOD TO RESOLVE PROBLEMS

However, this pollination system presents some limitations that must be addressed. For instance, drones and robots, replacing bees and humans, must be capable of searching and classifying flowers for pollination. Required technologies include mechanical control for making contact with the flower to pollinate it and communication technology for remotely controlling the drone or robot.

The main contributions of this study are as follows:

1) We propose a “search mode” for identifying flowers to be pollinated. In this flower-search technology, a drone discovers flowers through autonomous flight. Section II provides details of the AI classification technology for searching flowers [21], [22]. Accurate flight position location technology is required for a drone to fly autonomously. Therefore, we used motion-capture schemes for positioning technology [23]–[25]. Robot operation systems (ROS) were used for drone flight control [26]–[29]. Therefore, the proposed scheme integrates positioning and ROS to achieve autonomous flight control.
2) In the pollination working mode, the drone uses the same autonomous flight control as in the search mode. A vibrator device for pollination was developed and

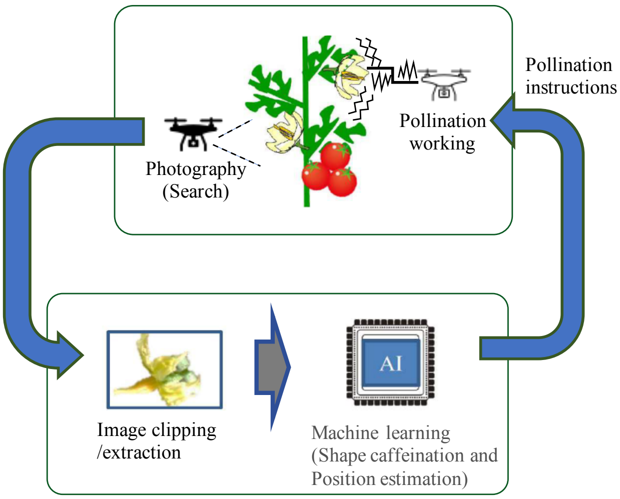


FIGURE 2. Pollination system configuration using small drones.

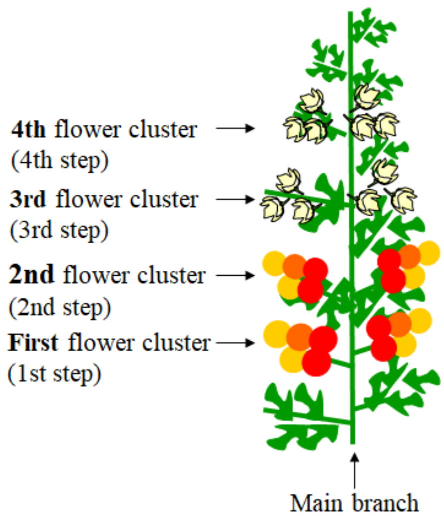


FIGURE 3. Flowering and Fruiting Steps.

implemented on the drone allowing it to pollinate flowers effectively during flight.

These two modes were linked as a series of operations, allowing the drone to perform tasks ranging from flower search to pollination. Finally, the drone was tested in a greenhouse tomato field to verify the fruiting rate.

In Section II, we provide an overview of AI classifiers, review related studies on flight control and positioning technology, and discuss these problems. In Section III, we present the details of the technology used for the search and pollination modes. In Section IV, we present the experimental methods, flight-control accuracy, and effectiveness of the pollination oscillator. Finally, we conclude the paper and provide directions for future research in Section V.

II. METHODS COMPARISON AND RELATED WORKS

A. COMPARISON OF POLLINATION METHODS

Table 1 compares the proposed method of pollination of tomatoes using a drone system against the existing methods using insects (bees), manual artificial pollination using a vibrating device, and artificial pollination using synthetic plant hormones. Table 1 summarizes the pros and cons of these methods and corresponding related works.

Bee pollination is difficult to maintain because bees are living organisms that are inactive during high summer temperatures, making them unsuitable for pollination. Furthermore, as mentioned earlier, in some countries, using insects causes ecological risks. However, bee pollination is similar to natural pollination, so the hurdle to introducing it is low and easy to operate.

Manual pollination using vibrating devices is expensive and requires large numbers of workers during the summer when bees are inactive. It also requires skill in classifying the shape of flowers that can be pollinated, which is the biggest challenge in pollination methods. Despite these shortcomings, the fruiting rate is high because of reliable pollination by vibrating the flowers.

In contrast, artificial pollination using hormones involves concerns about the potential for drug-induced damage. When the insects are used in conjunction, insect damage must also be considered. Forced hormone pollination also affects the shape of the tomatoes, making it difficult to maintain quality. However, artificial pollination is simpler, easier to operate, and relatively inexpensive compared to manual pollination.

Finally, the proposed pollination method using a drone system is more expensive to implement than conventional pollination methods. Moreover, it is a complex technology with installation and maintenance issues. However, after installation, pollination is easy, and the reliability and fruit yield are equivalent to those of bees or manual pollination. Moreover, additional workers are no longer needed, and farm managers can reduce the time spent on the farm.

According to Table 1, the proposed method of using drones has increased costs but offers tremendous benefits and advantages. Therefore, our study has led to the research and development of a pollination system using drones. The technical challenges in pollination using drones and related works are described below.

B. AI CLASSIFIER FOR FINDING FLOWERS

In prior studies, we developed a technology for classifying pollable flowers through image analysis using drones [21], [22]. This classification method was designed using machine learning with a convolutional neural network algorithm [30], [31], popular for image analysis. It was developed as an AI classifier and modified for drone implementation as an elemental technology for the proposed pollination system. Fig. 4 illustrates the tomato flower transition from bud to bloom and fruit. Shape (a) represents a bud, whereas tomato fruits appear after shape (f). The fruiting rate of tomatoes was verified, and the flower shape enabling pollination was determined to be (d) with petals turned back. The exper-

TABLE 1. Pros and cons of pollination methods.

Method	Pros	Cons	Related works
Pollination by insects (Bees)	• Cultivation close to natural pollination • Conventional accustomed operations	• Difficult to maintain and manage insect • Decreased activity during high summer temperatures, i.e., lower pollination efficiency • Ecological risks	Ref. [12]–[14]
Pollination through manual using a vibrating device	• High pollination accuracy	• Worker flower classification skill requirements • Time-limited mass employment and worker costs	Ref. [15]–[17]
Pollination using synthetic plant hormones	• Easy Pollination Methods	• Use of inappropriate hormones can cause chemical damage • Decrease in fruit shape and taste (Quality problems)	Ref. [19], [20]
Pollination using drone systems	• Easy Pollination Methods • High pollination accuracy • No need to secure workers • Reduction of farmer's work hours	• High cost of implementing new systems • Installation and maintenance of existing fields	Ref. [21], [22]

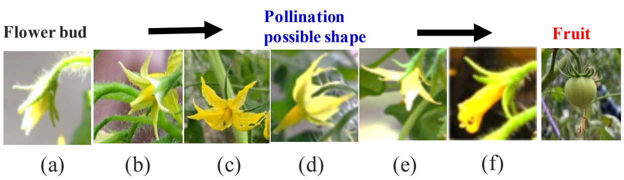


FIGURE 4. Flowering process.

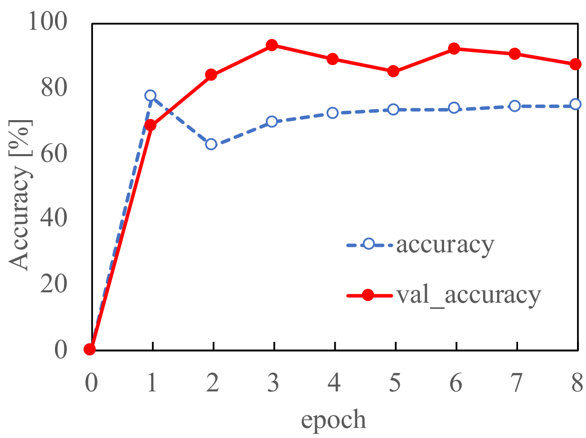


FIGURE 5. Learning result.

iment results confirmed that the flower shape (d) enabled pollination. The AI image classifier identified shape (d) from the captured image. Additionally, drone sway and vibrations caused by robot's movement affect images captured by drones and robots.

To simulate image blurring, a Gaussian filter was used to smooth the images for additional learning opportunities. The evaluation results obtained using the AI classification algorithm are shown in Fig. 5. The vertical and horizontal axes represent the accuracy rate (%) and the number of epochs, respectively. The solid and dashed lines represent the validation accuracy (val_accuracy) and training accuracy (accuracy), respectively. The evaluation results show that the number of epochs converged after eight, and the validation accuracy is 87.3%.

In Fig. 6, the horizontal axis displays the accuracy rate of shape (d) calculated using the AI classifier, and the vertical axis shows the fruiting rate. When the AI classifier accuracy rate is below 70%, the fruit set rate is approximately 40%; however, when the accuracy rate is above 70%, the fruit set rate exceeds 60%. These results indicate that pollination was generally successful when the AI classifier output accuracy was 70%. Therefore, we set the AI classifier threshold value to at least 70% as the value enabling pollination and implemented it in the drone developed in this study.

C. DRONE POSITIONING

Drone flight-control techniques can be classified into outdoor and indoor positioning techniques. The global navigation satellite system (GNSS) is the most used method for outdoor drone flight positioning. Various methods are employed by satellites to obtain high positioning accuracy. To achieve this, we acquired multiple position information and calculated the relative positions [32]–[34]. Additionally, instead of positioning based on signals from satellites, the wavelength of the received waveform is used to attain high positioning accuracy with an error of a few centimeters. This approach, known as interferometric positioning, involves satellites and ground-based reference stations for correction in conjunction with interferometric positioning. Moreover, RTK-GNSS provides real-time high-precision positioning for autonomous vehicles moving at high speeds along arbitrary routes [35], [36].

However, when using GNSS, it is essential to receive

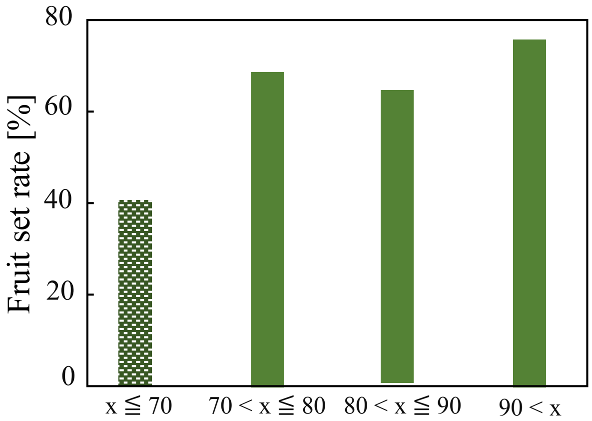


FIGURE 6. Threshold of accuracy rate obtained from fruit setting rate.

satellite signals reliably. In this study, we assumed tomato flowers would be pollinated in a greenhouse field; therefore, it was improbable that sufficient satellite signals would be received. Satellite positioning is the most popular drone positioning and flight-control system for outdoor use, and many related technologies and support systems are available to the public. However, positioning technology for drones in enclosed spaces, such as indoors, is less common. Furthermore, technologies and support systems related to flight control in conjunction with positioning technologies are less widely available than those for outdoor flights.

Common indoor positioning technologies include wireless local area networks and beacon systems [37]–[39]. These methods use the strength of the received power and the arrival time of wireless devices for positioning. However, in greenhouse fields, stems and leaves often interfere with radio waves, making highly accurate positioning difficult. Additionally, a wireless device for transmitting positioning signals must be mounted on a small drone. A small drone, which imitates a bee, should carry a little load to reduce power consumption, and the power for the positioning signal should be minimized. Another method is simultaneous localization and mapping, where a sensor mounted on a moving vehicle detects feature points in the environment and estimates its position by referring to registered map information [40]–[42]. It is unsuitable for greenhouses, where the shape of tomatoes changes as they grow. Additionally, mounting a sensor device on a drone poses the same payload and power consumption problems as wireless devices. The positioning accuracy ranges from several to tens of meters, and the positioning range is limited to only a few meters.

In this study, we used motion-capture technology with infrared cameras, considering the related problems [43]–[46]. Motion capture is an image positioning technique that employs triangulation techniques, with positioning accuracy ranging from a few millimeters to centimeters and a positioning range of several tens of meters. Therefore, it provides sufficient performance for drone flight control over a wide area with complex greenhouse geometries. The motion-capture system has the following features in terms of operation and functionality:

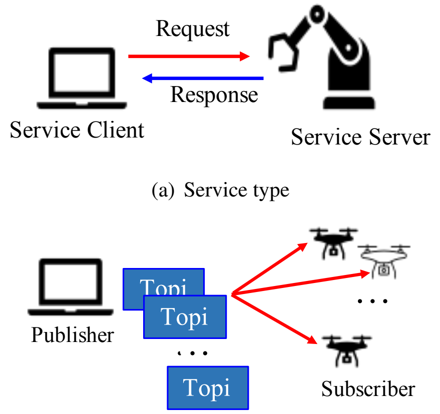
- #1 High-precision, non-contact, multi-point measurements
- #2 Ease of operation
- #3 Flexibility in designing a system for each object (camera arrangement device)

The signal strength can be ignored owing to radio noise or interference, and no dedicated device is mounted on the drone; thus, it provides advantages over other systems in payload and power savings. In related research, this technology has been employed to analyze body movements and study high-precision indoor autonomous flights [47], [48]. Specifically, an infrared camera was installed outside the flight range, and multiple cameras simultaneously observed the reflections from an optical marker attached to the aircraft for positioning. Optical markers are lightweight, which solves the problem of drone payloads, and do not require a signal to be transmitted, thus eliminating power consumption by the drone.

D. FLIGHT CONTROL AND ROS

A robot software platform called ROS is commonly used for drone flight control [26]. In this study, we implemented a specialized drone flight-control system using ROS. ROS is an application development support tool and software for robot control. It is a middleware that runs on a Unix-based OS and provides libraries for developing and executing robot application programs, such as data transmission and reception between multiple pieces of hardware, scheduling, and error handling. ROS uses nodes that are subdivided by function and purpose to increase program reusability. Nodes are the smallest processes implemented in ROS. The nodes communicate with each other through messages and data exchanges. There are two models for message communication: service type and publisher (Pub)/ subscriber (Sub) type.

1) Service Type
   As depicted in Fig. 7(a), the service type operates once a client wants to start, end, or execute a specific command. This method comprises a client that requests and a server that responds; the client determines if the request is successful. Therefore, the service type is a one-to-one synchronous communication, responding only when a request is received and disconnecting when the communication is over, thus minimizing the network load. For example, it is used when a robot performs a predetermined action or when a special event occurs under certain conditions.
2) Pub/Sub Type
   As depicted in Fig. 7(b), the Pub/Sub type operates by sending data called Topics to a Pub node and receiving the data from a Sub node. This method can control multiple robots because it involves simultaneous one-to-many asynchronous communications.



(a) Service type

(b) Sub/Pub type

FIGURE 7. Message communication method.

This study used the Pub/Sub type as a control technology for the ROS because it allows multiple drones to search for flowers simultaneously.

III. PROPOSAL AND CONFIGURATION OF POLLINATION SYSTEM

To develop a pollination system using small drones, we proposed an overall system configuration as illustrated in Fig. 8(a). The proposed system divides drone flight control into search and pollination working modes.

The rationale behind using two distinct modes is that searching for flowers is time-consuming and necessitates simultaneous control of multiple drones. For the pollination process, a different drone is used instead of the search drone. This is due to the separation of functions, allowing the pollination drone to directly move to the location of the identified flowers and perform pollination tasks. The payload of the pollination drone is heavier than that of the search drone, as it is equipped with a vibrator for pollination. Despite these differences, the same positioning and flight-control methods are employed for both types of drones.

In this study, motion-capture technology using an OptTrack infrared camera was used to position a drone within a greenhouse environment [49]. Multiple infrared cameras can detect reflective markers attached to the drones and compute their 3D coordinates. After determining the drone coordinates, it moves to the next coordinate to search for flowers. As depicted in Fig. 8(a), the flight-control node notifies the drone of its destination using the Launch command within the ROS library. This notification, called a Topic, is a predefined ROS function. The flight-control node acts as the publisher, and the subscriber drones receive notifications of the Topic. The ROS was pre-programmed to guide drones around tomato seedlings using the random waypoint method [50], directing them to fly to coordinates calculated by this method. More advanced search methods can also be efficiently implemented using swarm intelligence algorithms such as particle swarm optimization, ant colony optimization, and artificial bee colony [50]. These tasks can be effectively executed [51]–[53]. However, because the primary goal of this study is to verify the proposed method through implementation, the random waypoint method, which is simple to implement, was chosen. Detailed description of the search method is provided ahead in this paper, whereas the implementation of swarm intelligence algorithms will be the focus of future studies.

For the flower-search process, illustrated in Fig. 8(b), each drone is equipped with an ultra-compact camera that captures flower image data while in flight and transmits it to the AI classifier via the flight-control node. In this scenario, the drones act as the publisher and the flight-control node serves as the subscriber. AI classification has been extensively discussed in related studies on image coverage and quality [21], [22]. The AI classifier supplies the flight-control node with the flower locations suitable for pollination based on classification results. Following the search process, the AI system enters the pollination mode. The flight-control node supplies the specialized drone with the coordinates of the flowers that can be pollinated, along with flight instructions, and the drone performs the pollination task. As depicted in Fig. 9, the AI determiner during search mode only lists the flower coordinates suitable for pollination in the database and transfers these coordinates to the pollination working mode. In search mode, a Crazyflie2.1 [54] from Bitcraze was employed as an ultra-compact drone.

For the pollination working mode, we used a modified Tello [55] from Ryze Tech. Crazyflie2.1 is a palm-sized drone with dimensions of 92 mm width, 92 mm depth, 29 mm height, and 38 g weight (Fig. 10(a)). This drone is equipped with a camera for capturing images, a Wi-Fi module, and a marker frame for motion capture. The camera mounted on the drone has the same angle of view range and resolution as that used in the AI classifier [21]. In contrast, Tello has dimensions of 98 mm width, 92.5 mm depth, 41 mm height, and 80 g weight (Fig. 10 (b)). It employs a drone with a larger payload capacity to accommodate the pollinator required for the pollination working mode. The search and pollination drones are equipped with four markers that reflect the infrared light emitted by the camera. Two or more cameras are used to locate the reflected light and calculate the center of gravity and marker coordinates. The search drone was also equipped with a camera for taking pictures of flowers. The image data and flight instruction information were transmitted via Wi-Fi. The onboard pollinator features a vibrating machine in the pollination working mode, as illustrated in Fig. 10(b). A detailed description of the vibrating machine is provided in the preceding section.

IV. EXPERIMENTAL CONFIGURATION AND PERFORMANCE EVALUATION

The proposed system was implemented on drones, and its performance was evaluated through flight experiments in a tomato field. A frame with an infrared camera was con-

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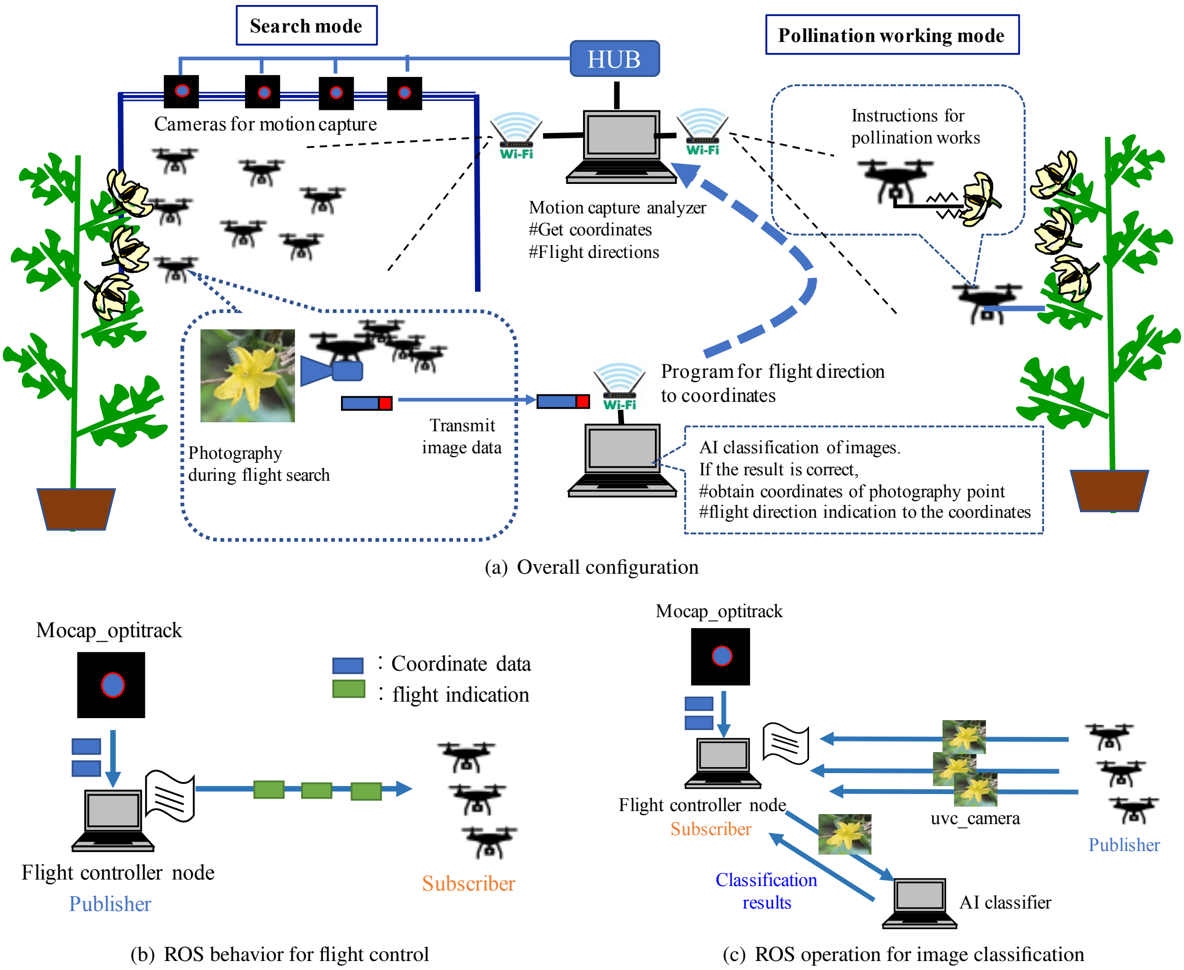


(a) Overall configuration

(b) ROS behavior for flight control

(c) ROS operation for image classification

FIGURE 8. Configuration of pollination system.

structed in the tomato field, as illustrated in Fig. 11. The frame spanned the pathway and had a width (W) of 2 m, depth (L) of 3 m, and height (H) of 2 m. The flight range of the drone was within the frame. Fig. 12 illustrates the experimental configuration with the installed frame and infrared camera. In the search mode, the drone used the random waypoint method to search for flowers, which involved flying around the tomato trunk. A computer simulation was performed to evaluate the efficiency of the proposed search mode in identifying flowers, as depicted in Fig. 14.

As shown in Fig. 14(a), five flower positions (red points) were arbitrarily set at random, and a single drone moved through space along a horizontal axis of 1 m and vertical axis of 2 m using the random waypoint method. An average of 1000 simulations and random flower placements were conducted. When a drone flew within 0.1 m of a flower, assumed to be the image range of the camera mounted on the drone, its position was recorded in the database. The operation illustrated in Fig. 14(a) represents the all-search phase. Because only the approximate flower location is determined in this phase, the system transitions to the detailed search phase, as depicted in Fig. 14(b). In the detailed search phase, the system flies back and forth at 0.05 m intervals within a 0.3 m square around the flower locations identified in the all-search phase. During this flight, the system outputs 1 for the correct flag and coordinates when a flower is found and 0 otherwise. After completing the detailed search phase within the flight range, the center point of the coordinate that outputs 1 is determined, which is estimated to be the exact flower coordinates. Simultaneously, the AI classifier classified flowers. The search concluded after a detailed search of all flower locations found during all-search phases.

These flight operations are described by the flowchart in Fig. 13. First, the flight is initiated using the random waypoint. The flight control node instructs the takeoff. Next, a randomly selected first flight coordinate point is determined within the flight range of Fig. 14(a). The flight is divided into 10 segments up to that coordinate. This division method stabilizes the flight speed to move accurately from the start to the destination coordinate point. The flight instructions are issued to these calculated route coordinates. Next, we determine if the current coordinates are the final destination of the 10 segmented coordinates. If not, the process is repeated until the destination is reached. The drone repeats this operation

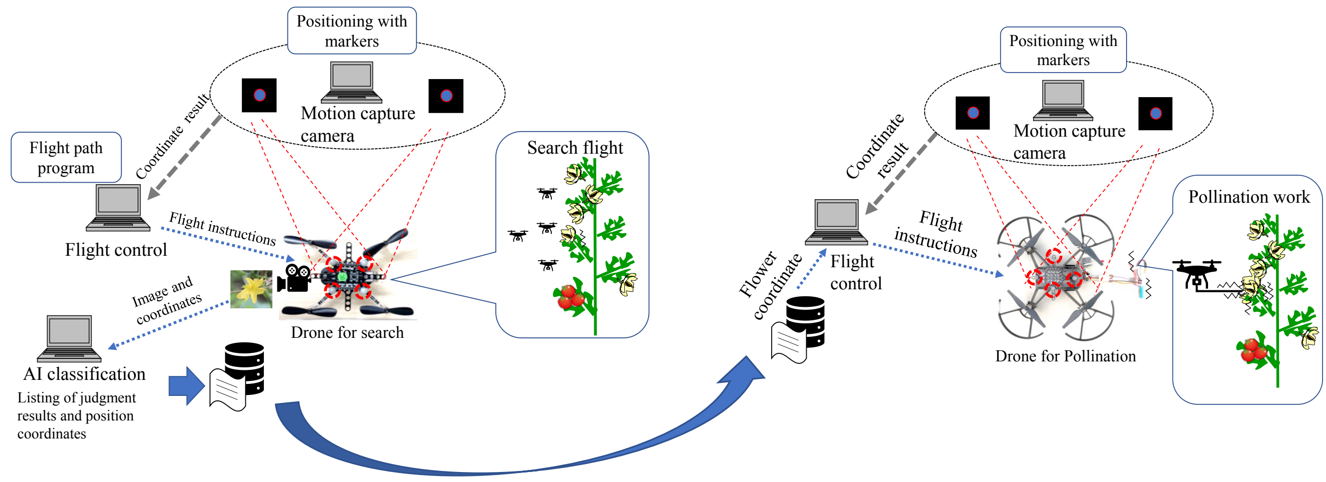


FIGURE 9. Coordination of searching and pollination.

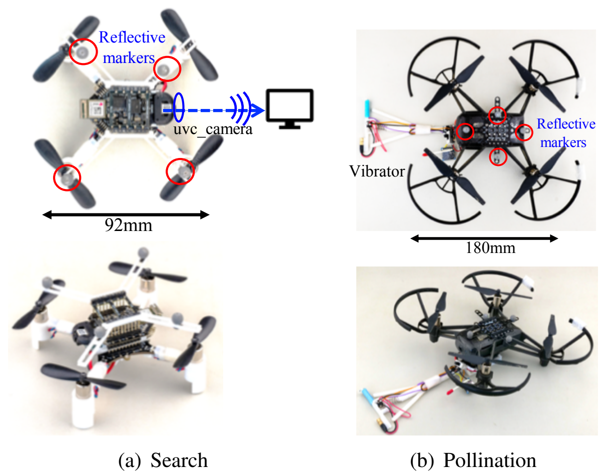


FIGURE 10. Search and pollination drones.

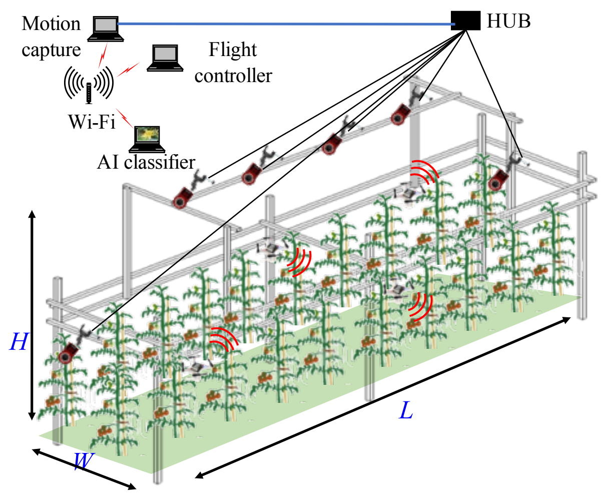


FIGURE 11. Frame with an infrared camera.

for a certain period. Although we can determine the flight method based on distance and not time, the flight time was set to 5 min considering the drone's battery capacity. These actions represent a rough search of the entire tomato trunk.

After completing the full search, the drone transitions to the detailed search operation. Detailed search computes the paths to search around the coordinates listed in the database in full search. The calculated paths are traversed back and forth as shown in Fig. 14(b) to determine if the search for the detailed search range has been completed. When this search range is finished, a detailed search is performed around the next listed coordinate. The all-search mode is terminated by issuing a landing instruction after all detailed search points listed are completed.

Once the takeoff command is issued, these procedures are automatically executed as a series of operations. The drone can fly autonomously without human intervention or the need to input commands as necessary.

Fig. 15 displays the results of evaluating the accuracy of flower location estimation using the search mode. The horizontal axis represents the distance of the estimation error, ranging from 0 to less than 10 mm, from 10 to less than 20 mm, and up to less than 60 mm. The vertical axis represents the cumulative results within the error range of the correct coordinates. The error ranges were approximately 37% for less than 10 mm, 24% for less than 20 mm, and 17% for less than 30 mm, with an overall error of approximately 80% within 30 mm. Correcting the flower positions in the pollination work mode was necessary for the error range to be nearly the same for drone implementation. A pollination vibrator was developed to address this.

Fig. 16(a) highlights the vibrator used for pollination. The vibrator consists of a T-shaped bar, the connection part of which is vibrated using a motor. The T-shaped part has a margin with a spring inserted to provide a movable range of motion when in contact with the flower, as depicted in Fig. 16(b). For instance, the T-shaped bar compensates for

FIGURE 12. Experimental configuration.

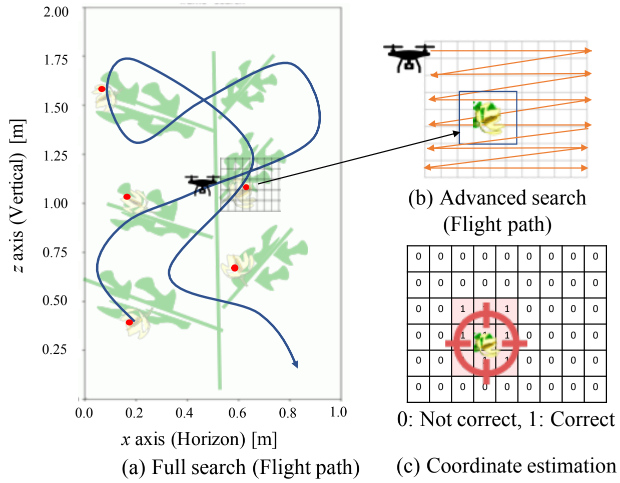


FIGURE 14. Flight procedure for search mode.

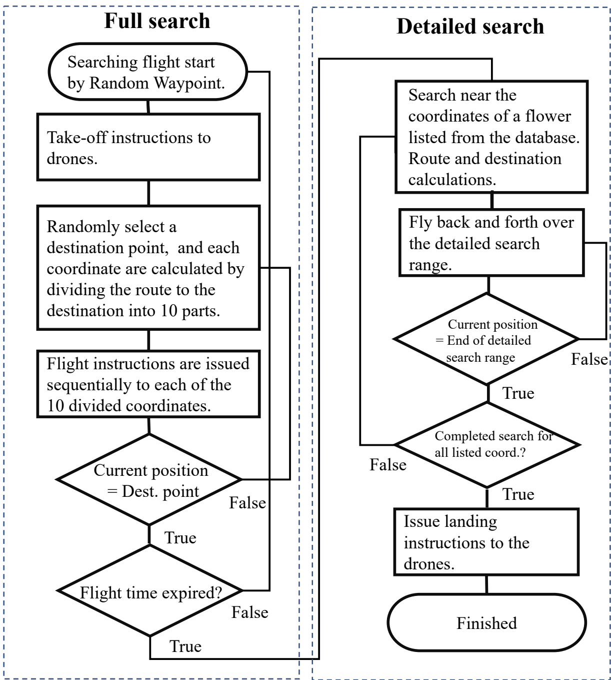


FIGURE 13. Flowchart of search mode.

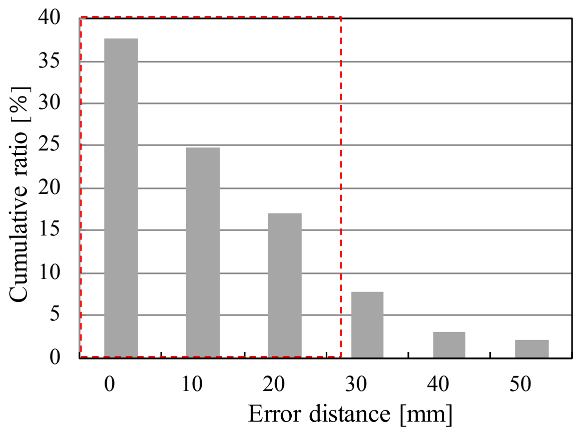
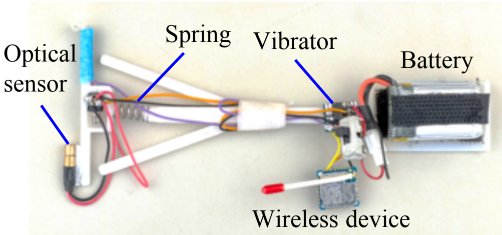


FIGURE 15. Flower position estimation accuracy.

the coordinate error in the flower position because it makes contact with the surface. The width of the top surface of the T shape is 55 mm, considering a margin based on an error range of 30 mm within 80% of the simulation results. The T-shaped connection length is 130 mm, which is the distance at which the drone's propeller would not come into contact with the leaves or trunk of the tomato plant. The weight of the pollination vibrator, including the battery, is 15 g, and the power consumption is 3.7 V at 81 mA. An optical sensor is attached to the upper surface of the T shape, and the vibrator automatically vibrates when in contact with the flower. The optical sensor is wirelessly connected to the flight-control node. If the flower detection is incorrect or the T junction cannot contact the flower, the sensor does not send a contact signal to the flight-control node. Then, the algorithm aborts the pollination process, moves to another flower location, and resumes pollination. Fig. 17 illustrates an experimental scenario of search and pollination in the field.

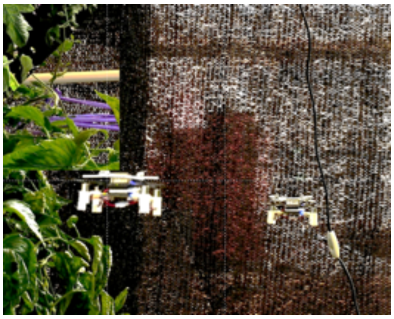
Finally, the performance of the pollination vibrator was verified By evaluating the fruiting rate when performing pollination using the proposed vibrator (Prop. Vibrator), bumblebees, and hormone treatments. The fruiting rate was defined as the percentage of pollinated flowers that became fruit. A pollination vibrator was used to vibrate the petiole for approximately 5 s on 200 flower clusters. The fruiting rates of the bumblebees are shown in Fig. 18(a). There is no significant difference between the fruiting rate of the bumblebees and that of the proposed pollination vibrator. The hormone treatment resulted in a slightly lower fruiting rate, confirming the superiority of physical vibration.



(a) Overall configuration

(b) ROS behavior for flight control

FIGURE 16. Pollination vibrator system.

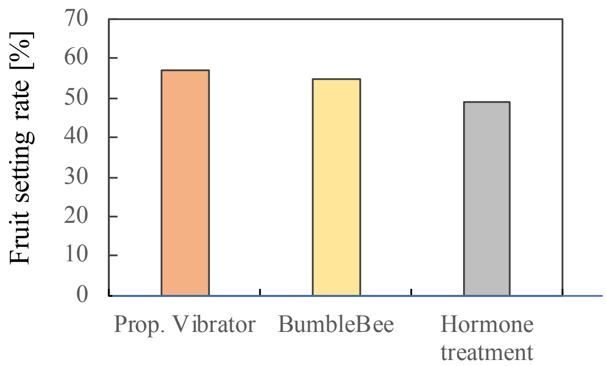


(a) Flower Searching

(b) Pollination works

FIGURE 17. Scene of the experiment.

These results demonstrate the effectiveness of the proposed pollination vibrator. The shape of the tomato fruits after fruit setting was also compared, as shown in Fig. 18 (a). The upper and lower rows show the shape of the fruit after treatment with the hormone and proposed pollination vibrator, respectively. Although this was a subjective evaluation, it



(a) Fruit setting rate for pollination method

(b) Shape quality comparison (Upper: Hormone, Lower: Vibrator)

FIGURE 18. Fruit setting and fruit quality.

was confirmed that the shape obtained using the pollination vibrator was close to a circle and of high quality. However, the results are not absolute as they vary depending on the outside air conditions and other factors. Therefore, future work will continue the verification process by conducting quantitative evaluations under uniform conditions such as ambient air.

V. CONCLUSIONS

We developed small drones as a substitute for bees to autonomously fly, search for flowers, and pollinate the discovered flowers. We also reported the experimental results using these drones. The drones were developed with flower-searching and pollination working modes. For the pollination working mode, we proposed a vibration machine with a structure designed to account for errors in the position of flowers detected in the search mode. The proposed system was validated through experiments and successfully implemented as an autonomous system that performs tasks ranging from flower search to pollination. The findings of this study can serve as a reference for future robot-assisted cultivation methods and systems.

However, the proposed system assumes that the field is currently in operation, which may limit operational conditions and cultivation efficiency. Robot and drone technologies are improving rapidly, and low-priced aircraft will become commonplace. Therefore, replacing bees with the proposed drone pollination system will contribute to smart agriculture. However, this experiment was conducted in a limited and restricted area, which is insufficient for operation in a large field. Challenges for practical application include short flight time due to the limited battery capacity of the drones, battery charge management for smooth operation, and service life and cost-effectiveness. However, this study aims to establish a drone control technology that autonomously searches for flowers and automatically pollinates them. In contrast, operational issues are obstacles that must be addressed for the system to be marketed as a service and commercialized as a product. We leave these issues for future work.

In addition, changes in illumination may reduce the classification accuracy of the AI classifier. For example, when experiments were conducted in the field from morning to evening, classification accuracy was reduced in some cases due to the amount and angle of sunlight in the greenhouse. Therefore, the time of day and weather conditions during which the drones search for the best flowers will be discussed in future work.

Based on these findings, we plan to expand this research by proposing a new cultivation method, preparing fields with environments suitable for drones and robots, and suggesting alternative cultivation techniques and approaches. This will help develop more efficient and adaptable robotic systems for agricultural applications.

SUPPLEMENTARY MATERIAL

Demonstration experiments of the drone bee system in a laboratory and tomato field in a greenhouse is available as supplementary video material. This video also can be viewed on YouTube at https://www.youtube.com/watch?v=OVtBr70ExWw

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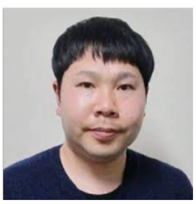

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