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# A Voronoi Diagram-Based Workspace Partition for Weak Cooperation of Multi-Robot System in Orchard

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**ABSTRACT** Nowadays, multi-robot systems are being utilized to perform agricultural tasks. It is particularly essential to robotize pesticide spraying because of the risk of poisoning workers. However, the problem is that the human-driven sprayers are big size, and difficult to maneuver in many orchards. Therefore, heavy spraying robots must be replaced with lighter robots. Also, it takes a lot of times to perform spraying using only one sprayer in a large orchard. To achieve this goal, the multi-robot system (MRS) can be applied to the spraying by robot cooperation to improve performance. In this study, we developed a task allocation system based on a Voronoi diagram for a multi-robot spraying system in an orchard. The seed point for area partition using the Voronoi diagram was obtained through node clustering using a $k$-means clustering algorithm. In the experiment, workspaces were partitioned according to the number of robots, from 2 to 10. A total of four metrics were used to evaluate the performance of the system. The results confirmed that our task allocation system is applicable to real orchards.

**INDEX TERMS** Agricultural robot, multi-robot system, task allocation, area partition, unmanned ground vehicle (UGV).

## I. INTRODUCTION

Pesticide spraying significantly improves crop productivity, and must be performed in orchards, especially because pears and apples are susceptible to infection. In orchards, pesticide spraying is performed by a worker driving a speed sprayer (SS) or spraying the fruit with a crop sprayer. This method of spraying exposes the worker directly to pesticides and could result in fatal pesticide poisoning. Considering the health risks faced by workers when spraying pesticides, the crop protection could be a significant application for robotics. Several studies have been conducted on the use of robots for spraying to reduce the risk of pesticide poisoning for workers [1]–[5]. However, the problem is that the human-driven sprayers are huge, with an elevated center of mass that is instability-prone, and difficult to maneuver in many orchards. Therefore, the heavy spraying robots must be replaced with more intelligent and lighter robots. Also, it takes a lot of costs and times to perform spraying using only one sprayer in a large orchard. To achieve this goal, the multi-robot system (MRS) can be applied to the spraying by robot cooperation to improve performance.

As the number of agricultural workers continues to decrease around the world, the use of MRSs for performing agricultural tasks is becoming more prevalent on large-scale farms with fewer people [6]–[16]. Division of work through cooperation among MRSs is increasing the productivity of farming households and the yield per unit area. As the work can be carried out more efficiently, potential for utilization is increasing through many related studies [17]. In agriculture, multi-robots are currently being utilized in various applications such as mapping [18], [19], seeding [20], sensing [21], [22], and pesticide spraying [23], [24].

To apply the MRS to agricultural tasks, multi-robot task allocation (MRTA) should be performed to distribute each task to the robots. MRTA is one of the most challenging problems of MRS, i.e., how to optimally assign a set of tasks to a team of robots in a manner that optimizes the overall system

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performance subject to a set of constraints [25]–[29]. The problem varies in time with events, including environmental changes, so the problem of task allocation is a dynamic decision that should be solved iteratively over time [30]. Therefore, the problem of MRTA should be approached more cautiously.

MRTA problems can be taxonomized along three axes [31], and this taxonomy help organizes MRTA problems and identify the theoretical foundations [32]. The first axis, single-task (ST) robots versus multi-task (MT) robots, distinguishes between problems in which each robot is capable of performing only one task at once and problems in which some robots can perform multiple tasks at the same time. The second axis, single-robot (SR) tasks versus multi-robot (MR) tasks. The SR can be expressed as weak cooperation [33], and it means that each task requires exactly one robot to complete it. In this case, the robots do not know each other's states and only perform their own tasks as assigned by the central control system. The MR can be expressed as strong cooperation [16], [34], [35], and it means that some tasks can require multiple robots. In this case, the robots communicate with each other and know their location and status. The third axis, instantaneous assignment (IA) versus time extended assignment (TA). The IA means that the instantaneous allocation of the tasks to the robots without planning future allocation. The TA means that each robot is allocated several tasks that must be executed according to a given plan.

In this study, a MRTA system was designated ST-SR-IA. In the case of spraying, it is not necessary for several robots to collaborate to spray one tree; instead, only one robot sprays one tree. Therefore, there is no need for communication between robots, and each robot only needs to receive commands from the central control system about its own driving path to do the spraying. Our approach for MRTA is partitioning the workspaces according to the number of robots, assign each sub-area to the robot, and then control the robot to perform spraying in its zone. The sub-area assigned to each robot does not change over time. The workspace partition is performed by using the Voronoi diagram [36], [37].

This paper is organized as follows: Section II introduces related work of task allocation for multi-robots and multi spraying robots. Section III describes the our MRTA system for the spraying task. Section IV and V provide experimental results to demonstrate the feasibility of our approach. Section VI describes a brief discussion of future work. Finally, Section VII concludes with a summary of our contributions.

## II. RELATED WORKS

### A. RELATED WORKS IN MRS FOR SPRAYING

Applying an MRS to a wide orchard can effectively spray the orchard in a short amount of time and with less labor [38]. In [39], a multi-robot cooperative approach have been proposed a strategy by which a team of robots could cooperatively perform area coverage related tasks in a known environment. The focus of this approach is to perform task allocation and coordination using only the robots' local position information. Therefore, since local perceptions of the robots are limited, the distance between two consecutive locations cannot exceed beyond the robots' range of detection.

In [24], project RHEA designed and developed a new generation of automatic robots for effective weed management in agriculture in both the chemical and physical domains. The UGV, which equipped with sensors, onboard perception systems, controllers and communication systems, were configured autonomous robots capable of carrying agricultural implements. The hex-rotor drone were designed to carry a two-camera perception system to perform remote detection of weed spots on narrow-row crops. Both types of vehicles were demonstrated with complementary features to work collectively.

In addition, [40] have been proposed the formation control of a mobile robot following a leader based on Ultra Wide Band (UWB) technology, allowing the relative localization of two mobiles avoiding the limitations of GPS when moving close to high vegetation. However, this approach is the way follower robots follow the leader, so there is a problem that if a leader becomes non-workable status, followers also cannot task either. And also, it is difficult to apply if there are more than three robots.

### B. RELATED WORKS IN THE VORONOI DIAGRAMS BASED MRTA

A Voronoi diagram divides the areas according to which points are closest to the seed points. Voronoi diagrams are commonly used to allocate multi-robot paths or workspaces, and a variety of current studies have been conducted on this topic [41]–[43].

In [44], a constrained centroidal Voronoi tessellation on a coarse approximation of the surface to cover has been proposed. This approach significantly reduces the probability of being trapped in local optima far from the globally optimal solution. At the same time, the number of repetitions of measurements and calculations required for the algorithm to converge is also lower. This advantage can be significant for the success of missions in complicated environments where unmanned aerial vehicles (UAVs) with limited energy are employed.

The coverage control algorithms for a group of networked robots have been presented that achieve discrete Voronoi coverage on a surface mesh [45]. The algorithm approximates the Voronoi regions by mesh cells and locally reassigns cells to neighboring areas to minimize the cost of the overall Voronoi configuration. The analysis of experimental results has been shown as a measure such as the convergence rate, suboptimal local minimum, the cost of the final configuration, and the initial configuration.

In [46], an approach has been proposed to solving the Multi-robot Informative Path Planning (MIPP) problem under communication limitations in unknown environments

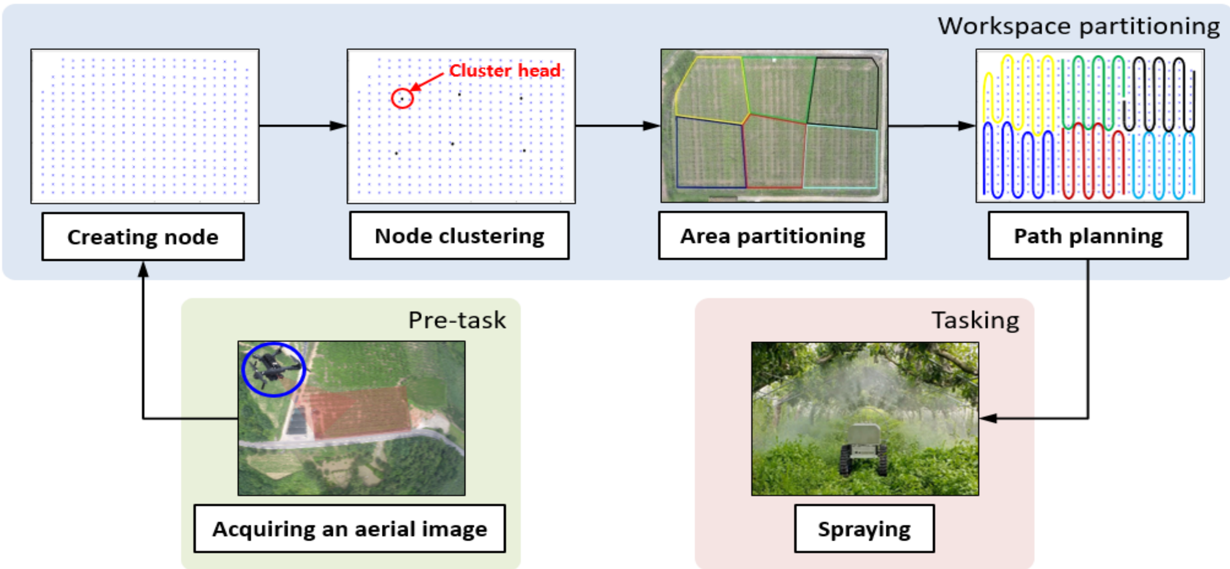


**FIGURE 1.** The global system flowchart of MRTA for spraying task.

using a Voronoi-based method. This approach aims to separate the area among the robots for better load-balancing and minimized unnecessary information acquisition. Whenever a set of robots reach into each other's communication range, they repartition their Voronoi regions for better load-balancing.

In MRS, many issues can arise, such as robots directing towards the same unexplored workspaces and the possibility of robots crossing each other paths which may result in a collision. By using Voronoi diagrams in task allocation, we can overcome the issues mentioned above. This approach leads to efficient workspaces allocation for the exploration task and eliminates the possibility of cross paths since each workspace will not enter into another robots' Voronoi diagrams area. Each robot sprays a pesticide as it moves in its assigned workspace.

## III. TASK ALLOCATION FOR MULTI-ROBOT

In this section, we describe in detail of our MRTA systems. The goal of the MRTA system is efficiently allocating the whole orchard area to robots. Our MRTA systems for autonomous multi-robot spraying consisted of six steps.

Step 1 Acquiring an aerial image
Step 2 Creating node
Step 3 Node clustering
Step 4 Area partitioning
Step 5 Path planning
Step 6 Spraying

Figure 1 shows the global system flowchart. Initially, pictures are taken of target orchards using UAVs; these orchards are designated as "workspaces." Then, positions of nodes are designated from the obtained aerial images. The Voronoi diagram clusters the nodes to determine the center point as a seed point for partitioning the workspace to sub-areas. Path planning for spraying is then executed for each sub-area. Finally, each path plan is sent to the robots to be performed. In this research, we studied step 1 to step 4.

### A. CREATING NODE

Node creation is pre-work to be done before finding the seed point for Voronoi-based area partitioning. A single fruit tree is designated as a node in an orchard. The robot must pass by the node corresponding to the assigned area and perform spraying on the tree. So, the node forms the base for the path that the robot drives during path planning. Therefore, it is essential to specify the position of coordinates of the node.

To create a node, aerial images of the orchards are obtained using UAVs. Then, the fruit tree is designated as a node in the obtained aerial image and it is assigned coordinates $(x, y)$ from the nodes. After the aerial images are obtained, the position of the node is determining from the specific interval (density and pattern) of each tree of the orchard. Also, the altitude of the UAV should be known to determine the position of the node in the aerial images by using information about the specific interval of each tree.

### B. NODE CLUSTERING

To partition an area through a Voronoi diagram, a seed point in the center of the area is required. Node clustering by the $k$-means clustering algorithm must be performed first to designate seed points. The $k$-means clustering algorithm is one of the well-known clustering methods which have been studied in the last decades due to its simplicity [47]. $k$-means clustering involves partitioning the gathered data into $k$ groups of data. The $k$-means clustering algorithm looks for partitions to minimize the square error between the cluster's empirical mean and the cluster's point. The $k$-means algorithm is described in Algorithm 1.

**Algorithm 1** K-Means Algorithm

**input:** a dataset of points $X = \{x_1, ..., x_n\}$, a number of clusters $k$
**output:** centers $\{c_1, ..., c_k\}$ implicitly dividing $X$ into $k$ clusters
choose $k$ initial centers $C = \{c_1, ..., c_k\}$
**while** stopping criterion has not been met **do**
  assignment step:
  **for** $i = 1$ to $N$ **do**
    find closest center $c_k \in C$ to instance $x_i$
    assign instance $x_i$ to set $C_k$
    **for** $i = 1$ to $k$ **do**
      set $c_i$ to be the center of mass of all points in $C_i$
    **end for**
  **end for**
**end while**

where $c_j$ denote a cluster center, with $c_j \in \mathbb{R}^2, 1 \le j \le k$. The square error between the points inside $x$ and $c_j$ is determined by Eqs. (1), (2).

$$J(C_j) = \sum_{x \epsilon C_j} \left\| x - c_j \right\|^2 \tag{1}$$

$$J(C) = \sum_{j=1}^{k} \sum_{x \epsilon C_j} \left\| x - c_j \right\|^2 \tag{2}$$

where $k$ is defined as the number of multi-robots for spraying task.

### C. VORONOI DIAGRAM-BASED AREA PARTITIONING

Once the cluster centers of nodes have been defined, the cluster heads are become seed points and the workspaces are divided through the Voronoi diagram. The Voronoi diagram is a geometric structure that assumes the proximity (nearest neighbor) rule when associating each point, in the $\mathbb{R}^n$ space, to the site point closest to it [36]. The Voronoi diagram is an algorithm that indicates which points on the plane space are closest to which seed point for the given $k$, where the whole area is divided into $k$ sub-areas.

Define $G = \{g_1, ..., g_n\}$ as a collection of non-overlapping areas in the plane, and define $d(p, g_i)$ be the Euclidean distance between point $p$ and $g_i$, as defined in Eq. (3).

$$d(p, g_i) = \min_{q \in g_i} d(p, q) \tag{3}$$

where point $q$ exists within $g_i$ area. The Voronoi area $V(g_i)$ and the Voronoi diagram $V(G)$ are defined as follows:

$$V(g_i) = \left\{ p \in \mathbb{R}^2 \mid d(p, g_i) \le d(p, g_j), \quad \forall j \neq i \right\}. \tag{4}$$

$$V(G) = \left\{ V(g_1), \ldots, V(g_k) \right\} \tag{5}$$

The Voronoi diagram is an algorithm that indicates which points on the plane space are closest to which seed point for the given $k$, where the whole area is divided into $k$ sub-areas. Each of the $k$ robots is assigned to one sub-area, and the spraying task is carried out in each area by establishing a path plan. The path is created to pass by the node corresponding to the assigned area and perform spraying on the tree.

## IV. EXPERIMENTAL DESIGN

### A. PERFORMANCE METRIC

We evaluated our system to confirm that it applies to a variety of orchard environments. We used a total of four performance metrics to evaluate the performance of our MRTA system. The metrics mainly focused on the performance of the system for the spraying task. The tasking time, computation time, coverage ratio, and segmented area ratio were used as the metrics.

Tasking time is defined as

$$T_T := \int_{t1_0}^{t1_c} dt \tag{6}$$

where $t1_0$ and $t1_c$ are the start and end times of the spraying task, respectively. The method of obtaining $T_T$ assumes that the route is arbitrarily specified in the assigned sub-area and that it takes the robot 2 s to spray one tree and 5 s to turn as it moves forward along this path.

Segmented area ratio is defined as

$$R_{SA} := (\frac{A_{sub}}{A_{total}}) \times 100 \tag{7}$$

where $A_{sub}$ is the area of the segmented sub-area.

Coverage ratio is defined as

$$R_C := (\frac{A_{total} - A_{overlap}}{A_{total}}) \times 100 \tag{8}$$

where $A_{total}$ is the total area of the orchard, and $A_{overlap}$ is the area that is not included in the tasking to prevent collisions between robots. We assume that a robot does not spray in areas that overlap with other robot's areas to prevent robot collisions.

Computation time is defined as

$$T_C := \int_{t2_0}^{t2_c} dt \tag{9}$$

where $t2_0$ is the start time of the computation and $t2_c$ is the completion time.

$T_T$ are the time factors for the robot to perform tasks in the orchard, and $R_C$ is a factor that shows the completeness of the task. As the values of these metrics increase, the task efficiency increases. Therefore, the higher the value, the better the performance. $T_C$ shows how the number of robots affects the computation time. $R_{SA}$ is an index of how evenly the sub-regions are divided.

### B. EXPERIMENT SETUP

Three pear orchards were used in the experiment, as shown in Figure 2. The orchards were located in Bonghwang-myeon, Naju-si, Jeollanam-do, Republic of Korea. Its location is 34°94'96''25N, 126°79'23''01W. The UAV used in the experiment was a quadcopter type UAV (3DR SOLO), to which an RGB camera was attached. The GoPro Hero

 

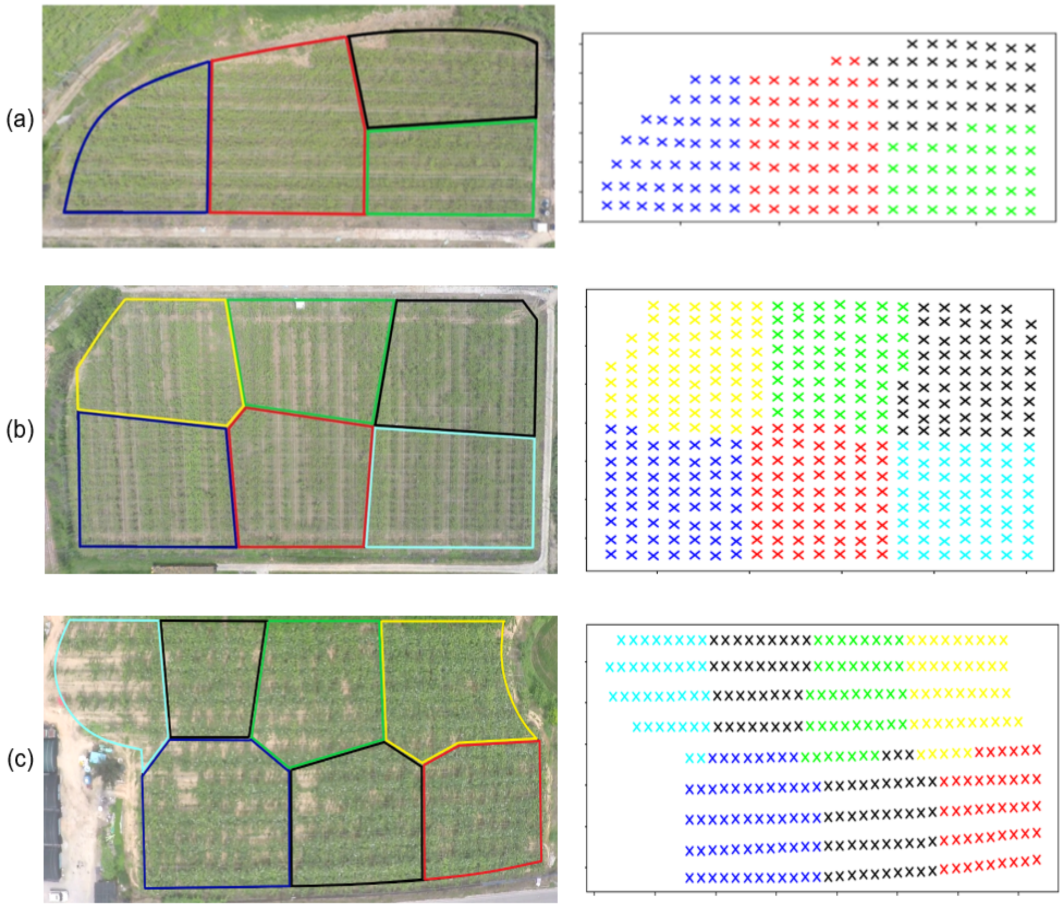


**FIGURE 2.** Area partition on different three pear orchards. Left: pictures illustrating the partitioned area. Right: nodes belonging to the sub-areas. (a) The first orchard which partitioned into 4 sub-areas (b) The second orchard which partitioned into 6 sub-areas (c) The third orchard which partitioned into 7 sub-areas.

4 model, which resolution is 3840 x 2160, was adopted as a camera for image acquisition. The UAV obtained images of orchards from an altitude of 120 m. The experimental environment was built to partition the workspaces through Python on a PC running Windows 10. When partitioning the workspaces, the number of robots was set for a total of 9 cases, from 2 to 10.

## V. EXPERIMENTAL RESULTS

The results for the performance metrics of the experiment are summarized in Tables 1, 2, 3 and Figures 4, 5, 6. Figure 2 shows the three pear orchards and the results of the sub-area partitioning (left) and the nodes belonging to the sub-areas (right). One of the orchards was partitioned into 2 to 9 sub-areas, as shown in Figure 3.

### A. TASKING TIME

$T_T$ is the time that the robot takes to do the task, and it is relevant to shortening the working hours. It is important to reduce the overall working time because the robot's battery consumption and the capacity of the pesticide tank can affect the robot's tasking time. The experimental results showed that $T_T$ decreases as the number of collaborative robots increases. These results indicate that using an MRS can increase work efficiency. In Table 1 and Fig. 4(a), comparing the $T_T$ of 6 robots to that of 7 robots, there was no significant difference in the respective values, indicating that the cost of too many robots outweighs their effectiveness. Therefore, it is important to apply the proper number of robots to orchards. Also, the number of robots should be determined by taking into account the cost of operating the robot, even if the overall tasking time is reduced.

### B. SEGMENTED AREA RATIO

$R_{SA}$ shows how evenly partitioned the sub-area is. In Table 1, $R_{SA}$ is most evenly partitioned when $k$ is 4 and most unevenly partitioned when $k$ is 3. In Table 2, $R_{SA}$ is most evenly partitioned when $k$ is 7 and most unevenly partitioned when $k$ is 2. In Table 3, $R_{SA}$ is most evenly partitioned when $k$ is 6 and most unevenly partitioned when $k$ is 4. According to these results, the value of $k$ does not significantly affect $R_{SA}$ in our system.

### C. COVERAGE RATIO

This metric should be considered when developing a system because it is very important in spraying. No matter how

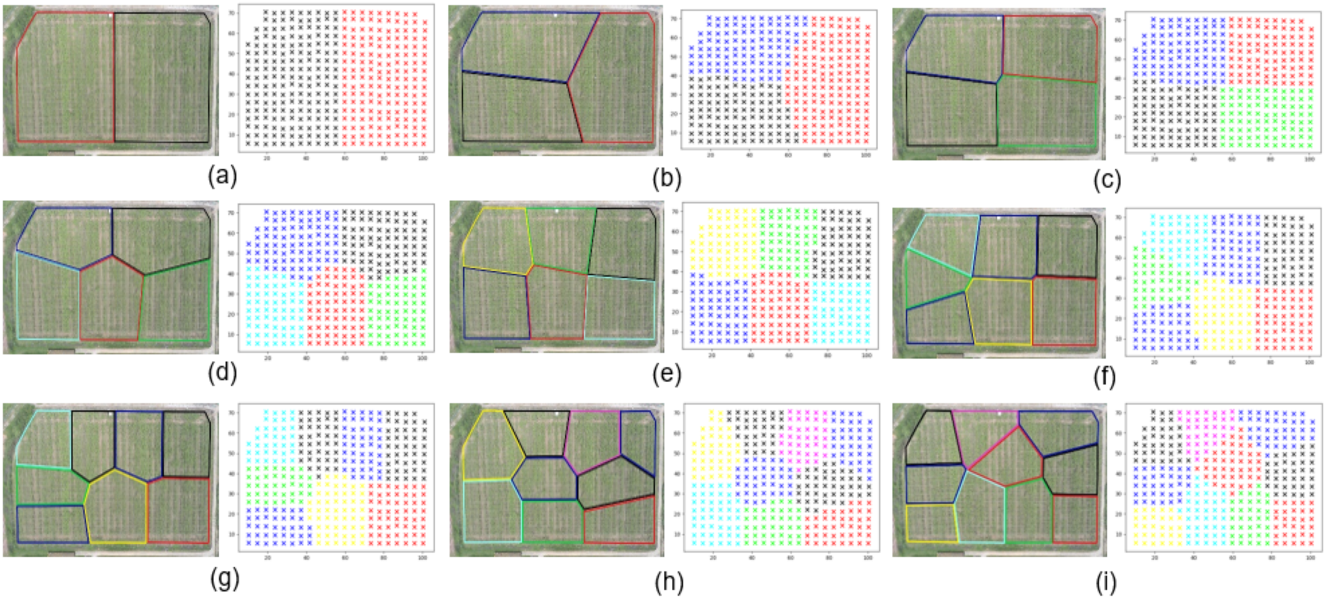

**FIGURE 3.** The second orchards was partitioned into 2 to 9 sub-areas. (a) 2 sub-areas (b) 3 sub-areas (c) 4 sub-areas (d) 5 sub-areas (e) 6 sub-areas (f) 7 sub-areas (g) 8 sub-areas (h) 9 sub-areas (i) 10 sub-areas.

**TABLE 1.** Results of experiments on the first orchard.

| Metric | | The number of robots | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| Tasking time (s) | individual values | 388 | 267 | 212 | 165 | 139 | 136 | 112 | 112 | 104 |
| | | 384 | 348 | 206 | 154 | 140 | 127 | 113 | 109 | 100 |
| | | | 254 | 231 | 144 | 130 | 136 | 126 | 109 | 83 |
| | | | | 205 | 190 | 147 | 150 | 121 | 115 | 96 |
| | | | | | 200 | 128 | 144 | 140 | 104 | 122 |
| | | | | | | 155 | 131 | 108 | 99 | 101 |
| | | | | | | | 142 | 108 | 94 | 125 |
| | | | | | | | | 142 | 122 | 99 |
| | | | | | | | | | 119 | 94 |
| | | | | | | | | | | 97 |
| | mean | 386 | 289.67 | 213.5 | 170.6 | 139.83 | 138 | 121.25 | 109.22 | 102.1 |
| | ± SD | ± 2.83 | ± 50.93 | ± 12.07 | ± 23.74 | ± 10.19 | ± 7.90 | ± 13.68 | ± 9.11 | ± 12.62 |
| Segmented area ratio (%) | individual values | 51.714 | 28.857 | 24.286 | 18 | 16.571 | 13.14 | 10.29 | 11.43 | 10 |
| | | 48.286 | 42.571 | 25.143 | 18.857 | 17.479 | 12 | 10.86 | 13.14 | 9.43 |
| | | | 29.714 | 25.143 | 17.714 | 16 | 12 | 10.86 | 9.43 | 8.29 |
| | | | | 25.427 | 23.143 | 18 | 15.43 | 11.43 | 10.29 | 9.71 |
| | | | | | 22.286 | 15.514 | 16.29 | 15.43 | 10.86 | 11.71 |
| | | | | | | 16.286 | 15.14 | 12.57 | 10.86 | 11.14 |
| | | | | | | | 16 | 12.57 | 10.29 | 11.14 |
| | | | | | | | | 16 | 12 | 10.29 |
| | | | | | | | | | 11.71 | 10 |
| | | | | | | | | | | 8.57 |
| | mean | 50 | 33.3333 | 25 | 20 | 16.6667 | 14.2857 | 12.5013 | 11.1111 | 10 |
| | ± SD | ± 2.42 | ± 7.68 | ± 0.49 | ± 2.53 | ± 0.93 | ± 1.86 | ± 2.15 | ± 1.10 | ± 1.10 |
| Coverage ratio (%) | | 95.14 | 84.37 | 79.43 | 76.29 | 71.71 | 68.0 | 64.29 | 54.57 | 61.43 |
| Computation time (s) | | 0.0334 | 0.0555 | 0.0614 | 0.1127 | 0.1536 | 0.2101 | 0.2166 | 0.2366 | 0.3031 |

short $T_T$ is, if $R_C$ is low, the efficiency and accuracy of the spraying will be low too. In the experiment, the robot was not assigned to areas that overlap with other robots areas to prevent robot collisions. The experimental results on all three orchards showed that as $k$ increases, $R_C$ decreases except when $k$ is 10 in Table 1, and 6 in Table 3. This low $R_C$ figure is fatal to the efficiency of the task, thus it is essential to address it.

### D. COMPUTATION TIME

$T_C$ refers to the time it takes for the system to partition the area according to the number of robots, and this

**TABLE 2.** Results of experiments on the second orchard.

| Metric | | The number of robots | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| Tasking time (s) | individual values | 205 | 149 | 109 | 115 | 67 | 67 | 93 | 56 | 52 |
| | | 227 | 168 | 123 | 127 | 89 | 97 | 60 | 71 | 44 |
| | | | 185 | 137 | 108 | 99 | 97 | 56 | 53 | 51 |
| | | | | 157 | 103 | 124 | 62 | 100 | 57 | 53 |
| | | | | | 106 | 97 | 72 | 70 | 92 | 65 |
| | | | | | | 76 | 70 | 66 | 60 | 66 |
| | | | | | | | 78 | 65 | 68 | 60 |
| | | | | | | | | 47 | 60 | 63 |
| | | | | | | | | | 60 | 61 |
| | | | | | | | | | | 61 |
| | mean | 216 | 167.33 | 131.5 | 111.8 | 92 | 77.57 | 69.63 | 64.11 | 57.6 |
| | ± SD | ± 15.16 | ± 18.01 | ± 20.49 | ± 9.58 | ± 19.14 | ± 14.13 | ± 18.10 | ± 11.89 | ± 7.18 |
| Segmented area ratio (%) | individual values | 42.77 | 30.72 | 19.88 | 21.69 | 10.84 | 11.45 | 15.06 | 8.43 | 7.23 |
| | | 57.23 | 31.93 | 22.89 | 24.1 | 15.06 | 16.87 | 10.84 | 10.84 | 7.23 |
| | | | 37.95 | 27.11 | 18.67 | 16.87 | 15.66 | 9.64 | 10.24 | 9.04 |
| | | | | 30.12 | 17.47 | 22.89 | 13.86 | 17.47 | 9.04 | 9.64 |
| | | | | | 18.07 | 17.47 | 12.65 | 13.86 | 15.66 | 10.84 |
| | | | | | | 16.87 | 13.85 | 11.45 | 12.65 | 13.86 |
| | | | | | | | 15.66 | 12.05 | 11.45 | 9.64 |
| | | | | | | | | 9.64 | 12.05 | 13.86 |
| | | | | | | | | | 9.64 | 9.04 |
| | | | | | | | | | | 9.64 |
| | mean | 50 | 33.3333 | 25 | 20 | 16.6667 | 14.2857 | 12.5013 | 11.1111 | 10 |
| | ± SD | ± 10.22 | ± 3.87 | ± 4.52 | ± 2.81 | ± 3.90 | ± 1.89 | ± 2.77 | ± 2.19 | ± 2.31 |
| Coverage ratio (%) | | 90.96 | 82.53 | 72.89 | 68.07 | 61.45 | 58.43 | 57.23 | 50.60 | 48.19 |
| Computation time (s) | | 0.01272 | 0.0231 | 0.0295 | 0.0383 | 0.0701 | 0.0884 | 0.1107 | 0.1144 | 0.1221 |

**TABLE 3.** Results of experiments on the third orchard.

| Metric | | The number of robots | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| Tasking time (s) | individual values | 371 | 249 | 172 | 149 | 124 | 100 | 108 | 102 | 72 |
| | | 381 | 267 | 184 | 141 | 139 | 104 | 90 | 100 | 82 |
| | | | 269 | 203 | 175 | 141 | 136 | 102 | 107 | 90 |
| | | | | 243 | 162 | 137 | 106 | 100 | 88 | 78 |
| | | | | | 170 | 137 | 120 | 100 | 111 | 100 |
| | | | | | | 133 | 114 | 100 | 96 | 98 |
| | | | | | | | 117 | 112 | 90 | 109 |
| | | | | | | | | 107 | 82 | 87 |
| | | | | | | | | | 64 | 69 |
| | | | | | | | | | | 62 |
| | mean | 376 | 261.67 | 200.5 | 159.4 | 135.17 | 113.86 | 102.38 | 93.33 | 84.7 |
| | ± SD | ± 7.07 | ± 11.02 | ± 31.08 | ± 14.22 | ± 6.08 | ± 12.17 | ± 6.72 | ± 14.38 | ± 14.94 |
| Segmented area ratio (%) | individual values | 49.15 | 30.72 | 21.84 | 18.43 | 16.04 | 11.95 | 11.95 | 11.26 | 7.17 |
| | | 50.85 | 34.81 | 23.21 | 17.75 | 16.38 | 11.60 | 11.60 | 12.29 | 8.53 |
| | | | 34.47 | 24.91 | 22.53 | 17.06 | 19.11 | 12.63 | 11.6 | 11.6 |
| | | | | 30.03 | 19.80 | 16.72 | 13.99 | 12.29 | 11.26 | 9.9 |
| | | | | | 21.50 | 16.72 | 14.68 | 12.29 | 12.63 | 10.92 |
| | | | | | | 17.06 | 14.33 | 12.29 | 12.63 | 12.29 |
| | | | | | | | 14.33 | 13.99 | 10.24 | 12.29 |
| | | | | | | | | 12.97 | 8.87 | 10.24 |
| | | | | | | | | | 9.22 | 8.53 |
| | | | | | | | | | | 8.53 |
| | mean | 50 | 33.33 | 25 | 20 | 16.67 | 14.29 | 12.5 | 11.11 | 10 |
| | ± SD | ± 1.20 | ± 2.27 | ± 3.58 | ± 2.01 | ± 0.40 | ± 2.46 | ± 0.73 | ± 1.40 | ± 1.78 |
| Coverage ratio (%) | | 93.86 | 87.71 | 82.59 | 72.70 | 74.06 | 69.62 | 68.26 | 62.46 | 56.66 |
| Computation time (s) | | 0.0294 | 0.0508 | 0.0764 | 0.0992 | 0.1218 | 0.1479 | 0.2063 | 0.2236 | 0.2805 |

metric represents the basic performance of the system. The experiment results on all three orchards showed that the computation time increases as the number of robots increases. However, the difference between these figures has

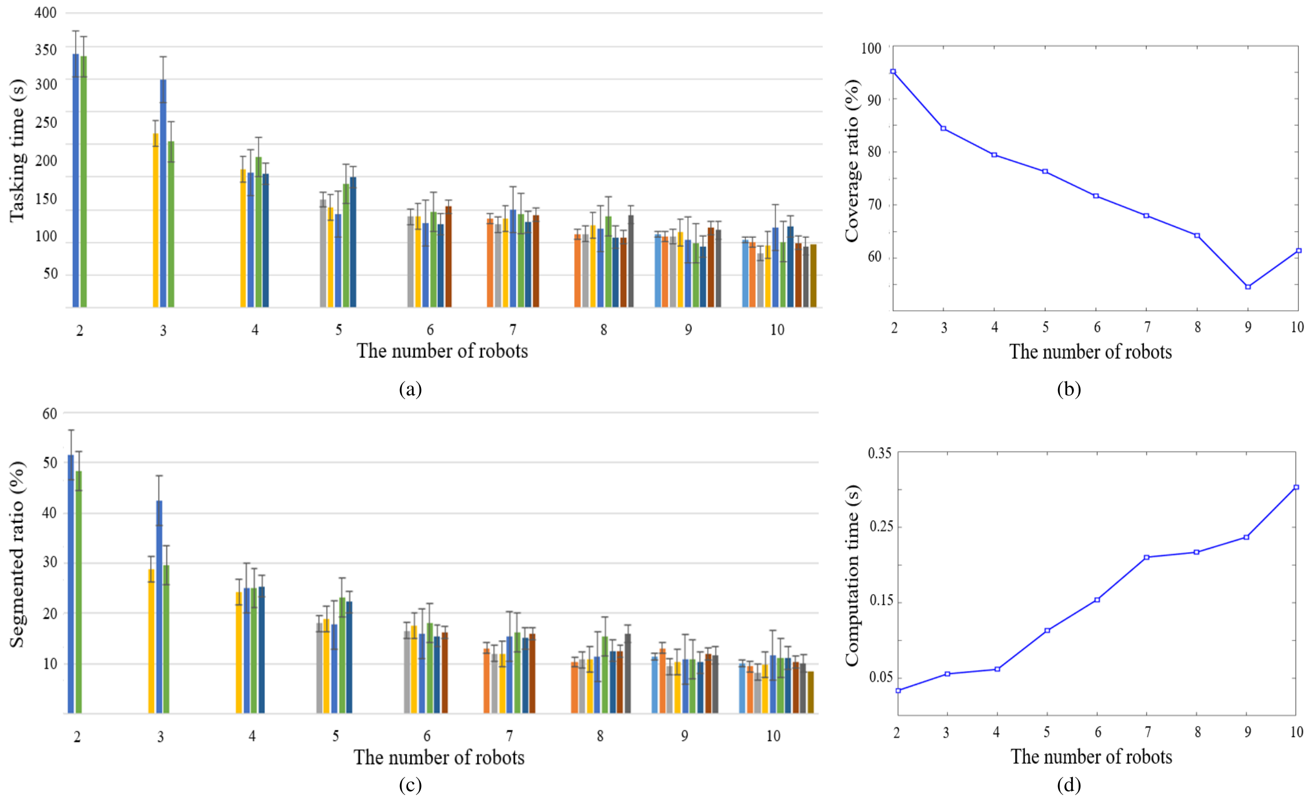


**FIGURE 4.** Results of experiments on the first orchard. (a) Tasking time (s) (b) Coverage ratio (%) (c) Segmented ratio (%) (d) Computation time (*s*).

no significant adverse effect on the performance of the system because it is the least important.

## VI. DISCUSSIONS

$T_C$ increases as the number of robots increases, but the variation is small and does not significantly affect the performance of the system. Because the degree of sub-area equality varies depending on the orchard, the value of $k$ does not significantly affect $R_{SA}$. As the number of robots increases, $T_T$ decreases but $R_C$ decreases. $T_T$ is very important in MRTA system and these results indicate that using an MRS can increase work efficiency. But no matter how short $T_T$ is, if $R_C$ is low, the efficiency and accuracy of the spraying will be low too.

Some limitations have to overcome to increase the performance of our MRTA system. To improve the performance of the system and expand the problem further, there are several factors to consider. As the number of robots increases, $R_C$ decreases. The $R_C$ is very important, because in real agricultural applications, not spraying parts of the orchard must be reduced as much as possible. To increase the coverage ratio, the path planning strategy for multiple robots should be extended to avoid collisions.

Therefore, optimization of the area partition and path planning is required to increase farm production when using multi-robots to carry out tasks and reduce working hours. If workspace partitioning and path planning are optimized by considering collision prevention and these factors among robots, an increase in the production of farms by multi-robots and reduced working hours are expected.

There is also a need to find out the optimal number of robots depending on the orchard environment. Since MRTA is ultimately aimed at minimizing the cost consumed, it is important to consider various factors to determine the optimal number of robots. The cost takes into account both the time it takes to work and the cost of running the robot.

### A. 3D AREA PARTITION

The experimental environment of this paper, the pear orchard, usually has flat ground, so there is no need to consider partitioning to 3D area. However, some orchards have extreme slopes or have different ground heights, which affect the robot's battery or speed. In this case, partitioning the areas in 3D should be considered. Firstly, a 3D ground mapping using UAVs can be performed by combining multiple overlapping 2D images of a target area. When 3D information on orchards is obtained, a partitioning of the areas can be performed considering the slope conditions on the ground.

### B. WEIGHTED VORONOI DIAGRAM-BASED AREA PARTITION

Another significant problem in the coordination of multi-robot systems is to maximize the degree of balance in the workload allocation within the multi-robot team [48], [49]. The multi-robot system should be displayed to its

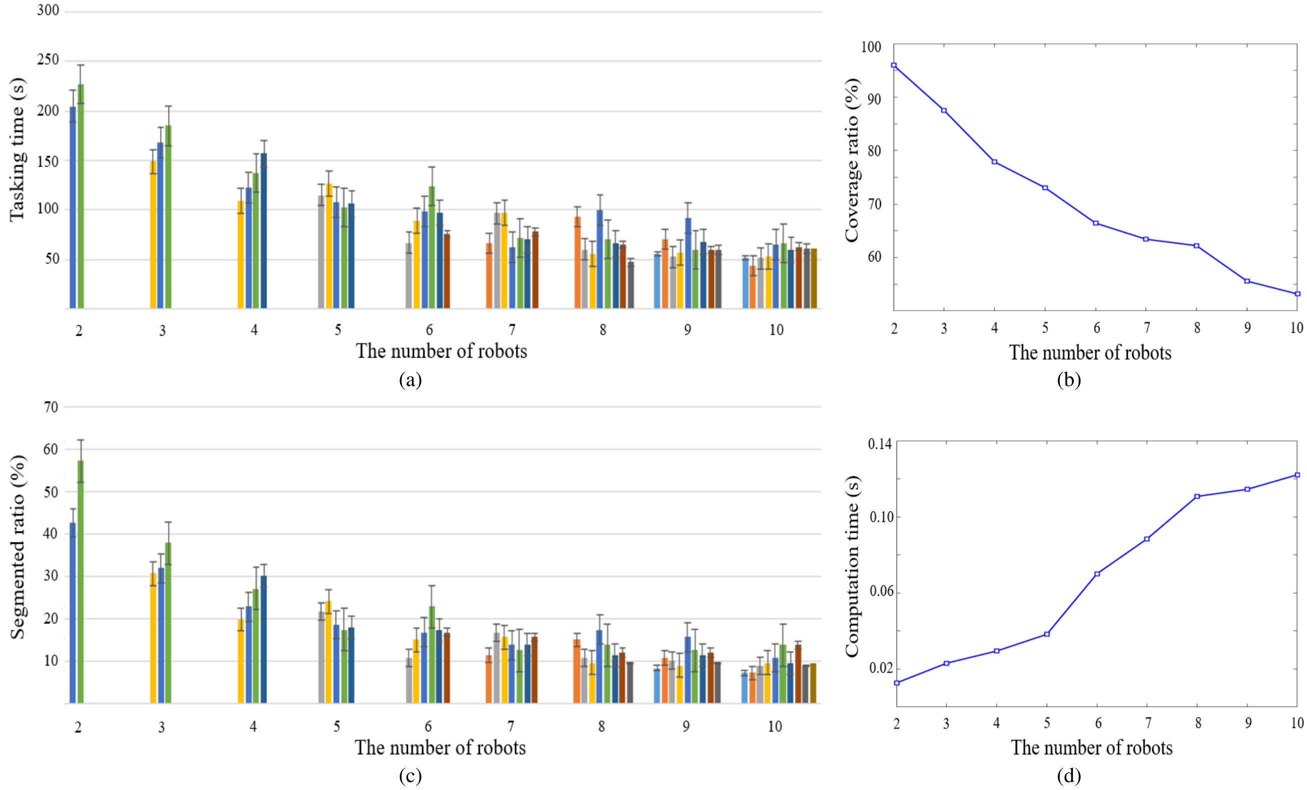


**FIGURE 5.** Results of experiments on the second orchard. (a) Tasking time (*s*) (b) Coverage ratio (%) (c) Segmented ratio (%) (d) Computation time (*s*).

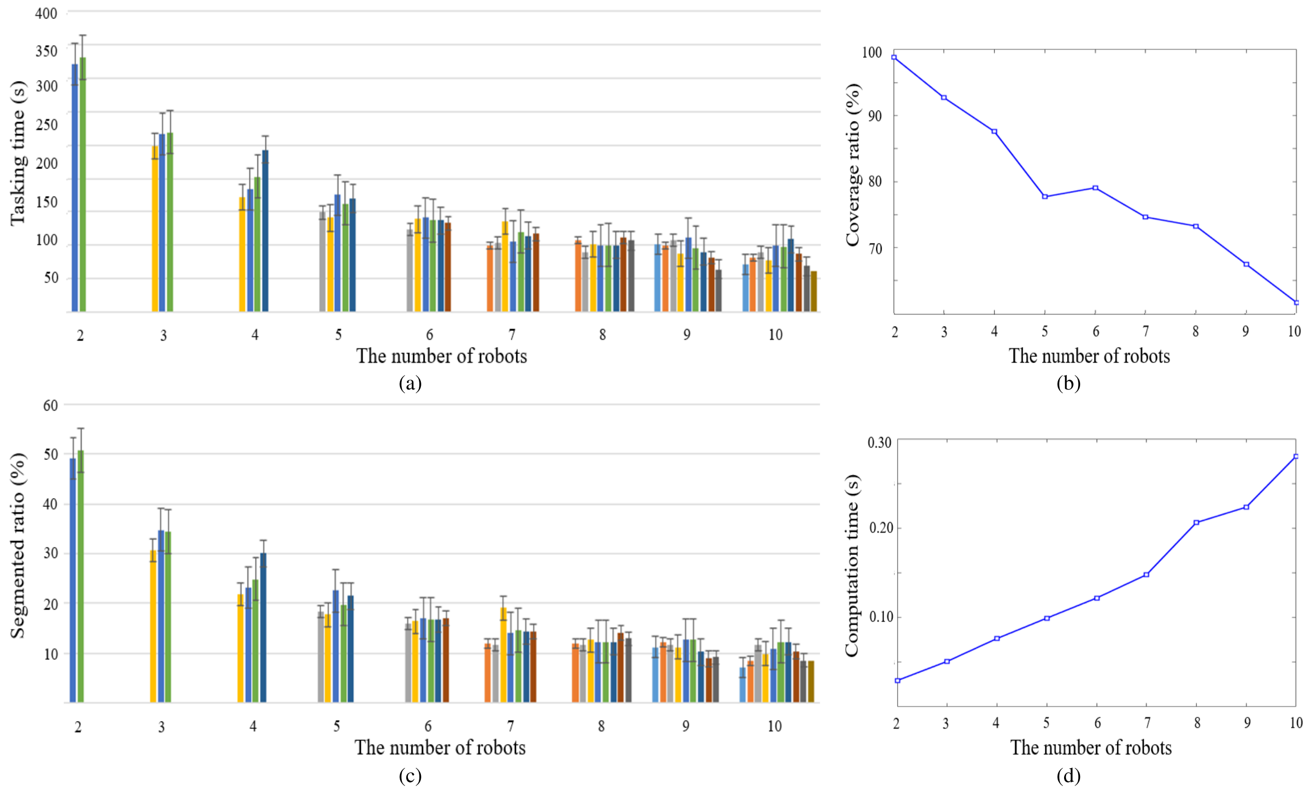


**FIGURE 6.** Results of experiments on the third orchard. (a) Tasking time (*s*) (b) Coverage ratio (%) (c) Segmented ratio (%) (d) Computation time (*s*).

actual potential by load balancing. To optimize and balance the area partitioning of a multi-robot, many things need to be considered, including the state of the robot. To reduce the overall working time, the work area must be distributed according to the robot's initial location because it takes time for the robot to reach its workspace. In addition, if the multi-robot is a heterogeneous robot, the velocity, the battery, and the pesticide tank capacity are all different. These factors should also be considered because they affect the robot's working time and speed. In this case, the multiplicatively weighted Voronoi diagram can be applied for MRTA. The $w_i$ applied to the robot is determined by combining the above factors. The $w_i$ can be defined as Eq. (10).

$$w_i = w_i^l + w_i^v + w_i^b + w_i^c \tag{10}$$

where $w_i^l$ is the initial location of robot, $w_i^v$ is the velocity of robot, $w_i^b$ is the capacity of robot, and $w_i^c$ is the pesticide tank capacity of robot.

Thus, the multiplicatively weighted Voronoi area $V_{MW}(g_i)$ can defined as follows:

$$d_{MW}(p, g_i) = \frac{1}{w_i} \left\| X - X_i \right\| \ , w_i > 0. \tag{11}$$

$$V_{MW}(g_i) = \left\{ p \in \mathbb{R}^2 \mid d_{MW}(p, g_i) \leq d_{MW}(p, g_j) \ \ , \forall j \neq i \right\}, \tag{12}$$

This approach can increase the performance of MRTA. Considering only a few of these factors would make the area partition more efficient. Therefore, these approaches will produce evenly balanced assignments of the sub-areas to individual robots.

## VII. CONCLUSION

In this study, we developed a task allocation system for a pesticide-spraying multi-robot system based on a Voronoi diagram. The seed points for the area partitioning using a Voronoi diagram were obtained through node clustering using a $k$-means clustering algorithm. To evaluate the developed system, four performance metrics were used. In the experiment carried out to evaluate the system, workspaces were partitioned according to the number of robots, from 2 to 10. This experimental results lead us toward a final implementation on a team UGVs for spraying tasks in real orchard environments. Furthermore, we plan to extend the algorithms to provide collision avoidance guarantees to UGVs. It is also expected that our MRTA system can improve the efficiency of the spraying task using 3D area partition and multiplicatively weighted Voronoi-based area partition.

## REFERENCES

[1] P. J. Sammons, T. Furukawa, and A. Bulgin, "Autonomous pesticide spraying robot for use in a greenhouse," in *Proc. Austral. Conf. Robot. Autom.*, 2005, vol. 1, no. 9, pp. 1–9.

[2] Y. Ogawa, N. Kondo, M. Monta, and S. Shibusawa, "Spraying robot for grape production," in *Field and Service Robotics*. Berlin, Germany: Springer, 2003, pp. 539–548.

[3] C.-M. Wu and J.-T. Lu, "Implementation of remote control for a spraying robot," in *Proc. IEEE Int. Conf. Appl. Syst. Innov. (ICASI)*, May 2017, pp. 1010–1013.

[4] Z. Diao, C. Diao, and Y. Wu, "Algorithms of wheat disease identification in spraying robot system," in *Proc. 9th Int. Conf. Intell. Hum.-Mach. Syst. Cybern. (IHMSC)*, vol. 2, Aug. 2017, pp. 316–319.

[5] N. Nakao, H. Suzuki, T. Kitajima, A. Kuwahara, and T. Yasuno, "Path planning and traveling control for pesticide-spraying robot in greenhouse," *J. Signal Process.*, vol. 21, no. 4, pp. 175–178, 2017.

[6] J. J. Roldán, J. del Cerro, D. Garzón-Ramos, P. Garcia-Aunon, M. Garzón, J. de León, and A. Barrientos, "Robots in agriculture: State of art and practical experiences," in *Service Robots*. Rijeka, Croatia: InTech, 2017.

[7] K. R. Aravind, P. Raja, and M. Pérez-Ruiz, "Task-based agricultural mobile robots in arable farming: A review," *Spanish J. Agricult. Res.*, vol. 15, no. 1, Apr. 2017, Art. no. e02R01.

[8] F. Liebisch, J. Pfeifer, R. Khanna, P. Lottes, C. Stachniss, T. Falck, S. Sander, R. Siegwart, A. Walter, and E. Galceran, "Flourish—A robotic approach for automation in crop management," in *Proc. Workshop Comput.-Bildanalyse Unbemannte Autonom Fliegende Syst. Landwirtschaft*, vol. 21, 2016, p. 2016.

[9] C. Ju and H. I. Son, "Performance evaluation of multiple UAV systems for remote sensing in agriculture," in *Proc. Workshop Robotic Vis. Action Agricult. IEEE Int. Conf. Robot. Autom. (ICRA)*, Brisbane, QLD, Australia, May 2018, pp. 21–26.

[10] J. Kim, S. Kim, C. Ju, and H. I. Son, "Unmanned aerial vehicles in agriculture: A review of perspective of platform, control, and applications," *IEEE Access*, vol. 7, pp. 105100–105115, 2019.

[11] Q. Vu, M. Raković, V. Delic, and A. Ronzhin, "Trends in development of UAV-UGV cooperation approaches in precision agriculture," in *Proc. Int. Conf. Interact. Collaborative Robot.* Cham, Switzerland: Springer, 2018, pp. 213–221.

[12] C. Carbone, O. Garibaldi, and Z. Kurt, "Swarm robotics as a solution to crops inspection for precision agriculture," *KnE Eng.*, vol. 3, no. 1, pp. 552–562, 2018.

[13] A. Chevalier, C. Copot, R. De Keyser, A. Hernandez, and C. Ionescu, "A multi agent system for precision agriculture," in *Handling Uncertainty and Networked Structure in Robot Control*. Cham, Switzerland: Springer, 2015, pp. 361–386.

[14] C. Ju and H. I. Son, "A distributed swarm control for an agricultural multiple unmanned aerial vehicle system," *Proc. Inst. Mech. Eng. I, J. Syst. Control Eng.*, vol. 233, no. 10, pp. 1298–1308, Nov. 2019.

[15] J. A. Thomasson, C. P. Baillie, D. L. Antille, C. L. McCarthy, and C. R. Lobsey, "A review of the state of the art in agricultural automation. Part II: On-farm agricultural communications and connectivity," in *Proc. ASABE Annu. Int. Meeting*, 2018, p. 1.

[16] C. Ju and H. I. Son, "Hybrid systems based modeling and control of heterogeneous agricultural robots for field operations," in *Proc. ASABE Annu. Int. Meeting*, 2019, pp. 1–5.

[17] C. Zhang and N. Noguchi, "Development of a multi-robot tractor system for agriculture field work," *Comput. Electron. Agricult.*, vol. 142, pp. 79–90, Nov. 2017.

[18] J. Roldán, P. Garcia-Aunon, M. Garzón, J. De León, J. Del Cerro, and A. Barrientos, "Heterogeneous multi-robot system for mapping environmental variables of greenhouses," *Sensors*, vol. 16, no. 7, p. 1018, Jul. 2016.

[19] C. Potena, R. Khanna, J. Nieto, R. Siegwart, D. Nardi, and A. Pretto, "AgriColMap: Aerial-ground collaborative 3D mapping for precision farming," *IEEE Robot. Autom. Lett.*, vol. 4, no. 2, pp. 1085–1092, Apr. 2019.

[20] T. Blender, T. Buchner, B. Fernandez, B. Pichlmaier, and C. Schlegel, "Managing a mobile agricultural robot swarm for a seeding task," in *Proc. 42nd Annu. Conf. IEEE Ind. Electron. Soc. (IECON)*, Oct. 2016, pp. 6879–6886.

[21] A. Barrientos, J. Colorado, J. D. Cerro, A. Martinez, C. Rossi, D. Sanz, and J. Valente, "Aerial remote sensing in agriculture: A practical approach to area coverage and path planning for fleets of mini aerial robots," *J. Field Robot.*, vol. 28, no. 5, pp. 667–689, Sep. 2011.

[22] H. Chao, M. Baumann, A. Jensen, Y. Chen, Y. Cao, W. Ren, and M. Mckee, "Band-reconfigurable multi-UAV-based cooperative remote sensing for real-time water management and distributed irrigation control," *IFAC Proc. Volumes*, vol. 41, no. 2, pp. 11744–11749, 2008.

[23] R. Lal, A. Sharda, and P. Prabhakar, "Optimal multi-robot path planning for pesticide spraying in agricultural fields," in *Proc. IEEE 56th Annu. Conf. Decis. Control (CDC)*, Dec. 2017, pp. 5815–5820.

[24] P. Gonzalez-de-Santos, A. Ribeiro, C. Fernandez-Quintanilla, F. Lopez-Granados, M. Brandstoetter, S. Tomic, S. Pedrazzi, A. Peruzzi, G. Pajares, G. Kaplanis, M. Perez-Ruiz, C. Valero, J. Del Cerro, M. Vieri, G. Rabatel, and B. Debilde, "Fleets of robots for environmentally-safe pest control in agriculture," *Precis. Agricult.*, vol. 18, no. 4, pp. 574–614, Aug. 2017.

[25] A. Khamis, A. Hussein, and A. Elmogy, "Multi-robot task allocation: A review of the state-of-the-art," in *Cooperative Robots and Sensor Networks*. Cham, Switzerland: Springer, 2015, pp. 31–51.
[26] C. Ju and H. I. Son, "Modeling and control of heterogeneous agricultural field robots based on Ramadge–Wonham theory," *IEEE Robot. Autom. Lett.*, vol. 5, no. 1, pp. 48–55, Jan. 2020.
[27] H. I. Son, A. Franchi, L. L. Chuang, J. Kim, H. H. Bulthoff, and P. R. Giordano, "Human-centered design and evaluation of haptic cueing for teleoperation of multiple mobile robots," *IEEE Trans. Cybern.*, vol. 43, no. 2, pp. 597–609, Apr. 2013.
[28] A. Franchi, C. Secchi, H. I. Son, H. H. Bulthoff, and P. R. Giordano, "Bilateral teleoperation of groups of mobile robots with time-varying topology," *IEEE Trans. Robot.*, vol. 28, no. 5, pp. 1019–1033, Oct. 2012.
[29] D. Lee, A. Franchi, H. I. Son, C. Ha, H. H. Bulthoff, and P. R. Giordano, "Semiautonomous haptic teleoperation control architecture of multiple unmanned aerial vehicles," *IEEE/ASME Trans. Mechatronics*, vol. 18, no. 4, pp. 1334–1345, Aug. 2013.
[30] B. Gerkey and M. J. Mataric, "A framework for studying multi-robot task allocation," in *Proc. Multi-Robot Syst., From Swarms Intell. Automata*, vol. 2, 2003, pp. 15-26.
[31] B. P. Gerkey and M. J. Matarić, "A formal analysis and taxonomy of task allocation in multi-robot systems," *Int. J. Robot. Res.*, vol. 23, no. 9, pp. 939–954, Sep. 2004.
[32] G. A. Korsah, A. Stentz, and M. B. Dias, "A comprehensive taxonomy for multi-robot task allocation," *Int. J. Robot. Res.*, vol. 32, no. 12, pp. 1495–1512, Oct. 2013.
[33] X. Ma, F. Meng, Y. Li, W. Chen, and Y. Xi, "Multi-agent-based auctions for multi-robot exploration," in *Proc. 6th World Congr. Intell. Control Automat.*, vol. 2, 2006, pp. 9262–9266.
[34] N. Kalra, D. Ferguson, and A. Stentz, "Hoplites: A market-based framework for planned tight coordination in multirobot teams," in *Proc. IEEE Int. Conf. Robot. Autom.*, Jan. 2005, pp. 1170–1177.
[35] C. Ju and H. I. Son, "Multiple UAV systems for agricultural applications: Control, implementation, and evaluation," *Electronics*, vol. 7, no. 9, p. 162, Aug. 2018.
[36] F. Aurenhammer, "Voronoi diagrams—A survey of a fundamental geometric data structure," *ACM Comput. Surv.*, vol. 23, no. 3, pp. 345–405, 1991.
[37] J. W. Brandt and V. Algazi, "Continuous skeleton computation by Voronoi diagram," *CVGIP, Image Understand.*, vol. 55, no. 3, pp. 329–338, May 1992.
[38] J. Conesa-Muñoz, J. Valente, J. Del Cerro, A. Barrientos, and A. Ribeiro, "A multi-robot sense-act approach to lead to a proper acting in environmental incidents," *Sensors*, vol. 16, no. 8, p. 1269, Aug. 2016.
[39] A. Janani, L. Alboul, and J. Penders, "Multi robot cooperative area coverage, case study: Spraying," in *Proc. Annu. Conf. Towards Auto. Robot. Syst.* Cham, Switzerland: Springer, 2016, pp. 165–176.
[40] T. Tourrette, M. Deremetz, O. Naud, R. Lenain, J. Laneurit, and V. De Rudnicki, "Close coordination of mobile robots using radio beacons: A new concept aimed at smart spraying in agriculture," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Oct. 2018, pp. 7727–7734.
[41] J. Cortes, S. Martinez, T. Karatas, and F. Bullo, "Coverage control for mobile sensing networks," *IEEE Trans. Robot. Autom.*, vol. 20, no. 2, pp. 243–255, Apr. 2004.
[42] J. G. M. Fu, T. Bandyopadhyay, and M. H. Ang, "Local Voronoi decomposition for multi-agent task allocation," in *Proc. IEEE Int. Conf. Robot. Autom.*, May 2009, pp. 1935–1940.
[43] P. Dasgupta, A. Muñoz-Meléndez, and K. Guruprasad, "Multi-robot terrain coverage and task allocation for autonomous detection of landmines," *Proc. SPIE*, vol. 8359, Jun. 2012, Art. no. 83590H.
[44] A. Renzaglia, J. Dibangoye, V. L. Doze, and O. Simon, "Multi-UAV visual coverage of partially known 3D surfaces: Voronoi-based initialization to improve local optimizers," 2019, *arXiv:1901.10272*. [Online]. Available: https://arxiv.org/abs/1901.10272
[45] A. Breitenmoser, J.-C. Metzger, R. Siegwart, and D. Rus, "Distributed coverage control on surfaces in 3D space," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, Oct. 2010, pp. 5569–5576.
[46] A. Dutta, A. Bhattacharya, O. P. Kreidl, A. Ghosh, and P. Dasgupta, "Multi-robot informative path planning in unknown environments through continuous region partitioning," in *Proc. 32nd Int. Flairs Conf.*, 2019, pp. 1–4.
[47] K. Wagstaff, C. Cardie, S. Rogers, and S. Schrödl, "Constrained k-means clustering with background knowledge," in *Proc. ICML*, vol. 1, 2001, pp. 577–584.
[48] A. Gautam, S. A. Ram, V. S. Shekhawat, and S. Mohan, "Balanced partitioning of workspace for efficient multi-robot coordination," in *Proc. IEEE Int. Conf. Robot. Biomimetics (ROBIO)*, Dec. 2017, pp. 104–109.
[49] A. Gautam, V. S. Shekhawat, and S. Mohan, "A graph partitioning approach for fast exploration with multi-robot coordination," in *Proc. IEEE Int. Conf. Syst., Man Cybern. (SMC)*, Oct. 2019, pp. 459–465.

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