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RESEARCH ARTICLE

A Voronoi-Based Isotemporal Task Allocation System for Autonomous Tractor Fleet

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ABSTRACT This study proposes an isotemporal task allocation system for autonomous tractor vehicles to improve agricultural task efficiency. The proposed system integrates Voronoi-based workspace partitioning and isotemporal task allocation. The method performs isotemporal tasks by considering the performance and state (including distance, velocity, and fuel and battery capacity) of each tractor by adopting an optimal workspace partitioning method. Based on these factors, the system optimizes the sub-workspace allocation to minimize the task time deviation and ensure balanced workload distribution among heterogeneous robots. The proposed system is evaluated through numerical verification and field evaluation in an agricultural environment. The results of the field evaluation show that the task efficiency is significantly improved, such as a 25.88% reduction in total task time and a 92.89% reduction in task time deviation under optimized conditions. In addition, the similar results of the two evaluations indicate high consistency and performance maintenance of the proposed system performance. Through the proposed system, it can be easily applied to various tractor-based vehicle cooperative task models, and efficient task performance can be expected by reducing idle time and allowing tractors to perform the next task.

INDEX TERMS Agricultural robot, isotemporal task allocation, Voronoi diagram, workspace partitioning.

I. INTRODUCTION

Automation of agricultural systems is critical to improving productivity and ensuring sustainable food production. The introduction of autonomous tractors plays a key role in the advancement of agricultural system automation [1]. The autonomous tractors can perform various agricultural tasks without human intervention, which significantly improves operational efficiency, driver safety, and labor costs compared to manual tractors [2]. By integrating advanced Global Navigation Satellite System (GNSS)-based navigation systems, AI-based task scheduling, and precision agriculture technologies, autonomous tractors can perform field task with sub-centimeter accuracy, reducing input waste and improving crop yield efficiency [3], [4], [5]. Additionally, the rapid development of AI, the Internet of Things (IoT), and autonomous control systems has further accelerated the commercialization of these technologies, and major agricultural machinery manufacturers are implementing robust sensor networks, real-time kinematic (RTK) positioning, and machine learning-based adaptive control strategies [6]. Using real-time data analytics and adaptive multi-agent task allocation algorithms, autonomous tractors can dynamically adjust operating parameters based on soil conditions, crop growth stages, and environmental variables, creating a more sustainable and resource-efficient agricultural ecosystem [7].

The autonomous tractor fleet system that collaborates with multiple tractors is an efficient agricultural automation system that intelligently distributes tasks among tractors to further improve farm productivity and yield. The system applies advanced control algorithms, real-time

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communication networks, and sensor fusion to optimize operations and ensure efficient task execution. References [8] and [9] dynamically allocated tasks and coordinated operations between tractors through fleet technology to improve resource utilization, minimize overlapping task, and enhance farm productivity and yield. In addition, by integrating real-time data analysis and adaptive autonomous driving strategies, the tractor system can dynamically adapt to changing field conditions, improve decision-making, and improve operational efficiency [10]. This approach improves the accuracy of task execution and ensures strong adaptability to various terrain and crop conditions. This autonomous tractor fleet system contributes to the development of sustainable agricultural automation by optimizing fuel consumption, reducing emissions, and supporting precision agriculture technologies such as variable use of fertilizers and pesticides.

Extensive research on autonomous tractor vehicle technology has been conducted in the field of agricultural robots. Agricultural robotics research has been conducted in the context of heterogeneous swarm robot systems [11], [12]. Multi-robot task allocation (MRTA), Multi-robot path planning (MAPP), and cooperative control are required for swarm robot systems [13], [14]. For example, MRTA dynamically distributes work loads based on tractor performance, task priorities, and environmental conditions to avoid inefficiencies due to idle or overload. Path planning plans appropriate paths for tractors considering the dynamic structure of tractors, optimization of task time, etc. during agricultural task [15], [16]. Cooperative control enables multiple tractors to task cooperatively toward a common goal through advanced control algorithms and real-time communication systems, enabling synchronized movement and efficient achievement of common goals. A common approach in cooperative control is the leader-follower technique, where one or more tractors act as leaders and guide the movements of the follower tractors to ensure coordinated and efficient operation [17], [18]. The integration of these technologies is essential to improve the scalability and efficiency of autonomous farming systems.

In agricultural environments, optimal workload distribution directly affects vehicle efficiency, scalability, and overall field productivity by mitigating tractor overload and task time [19]. In addition, the improved workload allocation technique enhances agricultural machinery utilization through intelligent distribution strategies including optimized full-field coverage through computationally efficient path planning, adaptive workspace allocation based on field topography and soil heterogeneity, and energy-saving strategies [12], [20]. These methods ensure balanced workload distribution, minimize operational delays, and improve overall system throughput. The task allocation framework, which integrates mixed-integer linear programming (MILP) [21], heuristic-based optimization [22], and dynamic reallocation strategies, enables autonomous tractor vehicles to dynamically adapt to real-time environmental changes, unexpected disturbances, and operational uncertainties. Enhanced task allocation algorithms and optimization techniques create a scalable and robust foundation for autonomous tractor fleet systems to meet the evolving needs of modern precision agriculture.

In agricultural operations using autonomous tractor fleet, inherent differences in tractor performance and operating conditions (e.g., engine power, fuel economy, payload, initial position, mechanical reliability) pose significant challenges to achieving optimal efficiency. These differences can lead to imbalances in operational capabilities, complicating effective management of the overall operation. Furthermore, operational challenges are further exacerbated by external environmental factors such as soil conditions, crop maturity stages, and rapidly changing weather patterns common in agricultural environments. To address these challenges, an adaptive task allocation mechanism that utilizes accurate data analysis and allocation strategies to distribute appropriate tasks based on tractor performance and environmental conditions is essential. In addition, this strategy can mitigate workload imbalances, ensuring optimal utilization of high-performance tractors and preventing overloading of low-performance tractors. Such solutions can significantly improve synchronization between tractors, improve resource utilization, and maximize vehicle productivity and efficiency.

As mentioned earlier, to effectively address these challenges, a differential workspace partitioning task allocation system that optimizes the workspace allocation of individual tractors is essential. This system distributes the workload by considering the specific performance and current state of each tractor (e.g. engine power, fuel capacity, initial position), minimizing idle time, and ensuring balanced workload distribution across the vehicle. Furthermore, integrating this task allocation mechanism with autonomous systems allows for dynamic adjustments based on environmental conditions and operational feedback, effectively responding to unexpected obstacles, terrain changes, or task delays. This approach maximizes operational efficiency and improves vehicle-wide collaboration, enabling a scalable and robust autonomous tractor fleet system to address the challenges of modern agricultural environments.

This paper proposes a Voronoi-based isotemporal task allocation system to improve the operational efficiency of autonomous tractor fleet in agricultural environments. The proposed method combines Voronoi-based task space partitioning with an isotemporal allocation strategy to assign differentiated tasks that reflect the tractor's performance and state. This task allocation approach maximizes workload balance and overall efficiency through isotemporal task allocation that minimizes task completion times. The proposed method demonstrates its feasibility and applicability through numerical validation and field experiments in real agricultural environments, demonstrating both theoretical validity and practical applicability.

A. RELATED WORKS

1) AUTONOMOUS TRACTOR FLEET

In agriculture, researchers have developed multi-robot agricultural tractors (or vehicles) to reduce total work time and increase work efficiency [8]. Furthermore, a leader-follower system was developed to improve work efficiency for multi-robot tractor systems [23], [24], [25], [26]. [27] developed a team of robotic tractors to harvest peat moss. In this system, three robot tractors worked in three fields, and a human operator remotely commanded and monitored the robots. An agricultural multi-robot system (MRS) is similar to the sweep coverage robot system [28], [29], [30], [31], both of which must cover a large area in a minimum time. Recent advances have incorporated machine learning, computer vision, and communication technology, such as vehicle-to-vehicle (V2V) and vehicle-to-network (V2N) systems, to enhance adaptability, real-time coordination, and task optimization in dynamic environments. These innovations enable scalable, resource-efficient, and environmentally sustainable solutions for modern agricultural practices. However, in environments with limited communication, the risk of a robot leaving the communication zone and losing contact with other robots increases, resulting in duplicate task assignments, unnecessary exploration, and significantly increasing the overall task completion time.

2) MULTI-ROBOT TASK ALLOCATION

To effectively address these challenges, it is crucial to understand and optimize the fundamental problems of MRTA in complex environments [32]. In applying an autonomous tractor fleet to agricultural tasks, MRTA should be performed to distribute each task to the robots. MRTA optimally allocates a task set to a robot team to optimize the overall system performance subject to a set of constraints [33]. Several MRTA studies have proposed distributed approaches to address scalability issues and cooperative game theory [34]. Among these, market-based methods [35] utilize auction-like negotiation techniques and have proven successful in various domains [36]. Reference [32] conducted a study to optimize task execution time for spatially distributed and non-atomic tasks through a task allocation and scheduling model that allocates tasks considering a limited communication environment where robots rely on partial information. Graph neural networks have also been used for distributed multi-robot goal allocation [37]. These MRTAs often do not directly reflect the physical location relationship between robots and tasks. This can result in robots located far apart unnecessarily taking on distant tasks, which can increase travel distances and delay task start times. Furthermore, because task distribution considers the entire robot-task combination, computational complexity increases rapidly as the problem size increases.

3) VORONOI-BASED MRTA

The Voronoi diagram partitions an area according to a random point closest to the center. Voronoi diagrams are commonly employed to allocate multi-robot paths or workspaces, and studies have been conducted on this topic [38], [39], [40]. A limited central Voronoi tessellation for approximations of the surface to be covered has been proposed [41]. This approach considerably reduces the probability of being trapped in the local optima, which is far from the globally optimal solution. The number of iterations of measurements and calculations required for the algorithm to converge is also lower. This advantage can be significant for the success of missions in complex environments where unpiloted aerial vehicles (UAVs) with limited energy are deployed. A coverage control algorithm for a group of network robots achieving discrete Voronoi coverage in surface mesh is presented [42]. The algorithm approximates the Voronoi region with a mesh cell to minimize the cost of the entire Voronoi configuration, reallocating the cell locally to the adjacent region. The experimental results, such as convergence rate, local minimum of the lane, final configuration cost, and initial configuration, were analyzed on scales. Previous studies have proposed MRTA algorithms tailored for homogeneous and heterogeneous agricultural MRSs, using Voronoi-based methods for workspace partitioning and task allocation [43], [44]. However, a remaining critical limitation is that the resulting area partitioning is not optimally balanced or dynamically adaptable. The existing approaches often neglect essential operational constraints, such as energy consumption thresholds and temporal limitations, which are critical for guaranteeing robust and scalable MRTA implementations. Consequently, the current task allocation methods are limited in maximizing task efficiency while ensuring an equitable workload distribution across heterogeneous robotic systems [45], [46], [47].

B. CONTRIBUTIONS AND NOVELTY

The contributions and novelty of this study are summarized as follows:

1) The proposed isotemporal task allocation system is designed to allocate Voronoi-based partitioned workspaces for autonomous tractor fleets, minimizing idle time and balancing workload distributions.
2) The workspace partitioning that allocates sub-workspaces for each tractor is considered based on the performance and state of the tractors.
3) The isotemporal allocation that optimizes workspaces allocated on each tractor is allocated by reducing the overall task time and equalizing workloads.
4) A numerical validation and field evaluation verify the scalability, adaptability, and efficiency of the proposed system.

II. PROBLEM DESCRIPTION

In agricultural operation scenarios, the completion time of agricultural robotic vehicles is a critical factor, which is usually expressed as task execution time [48]. The workload distribution of each robot should be considered to ensure a

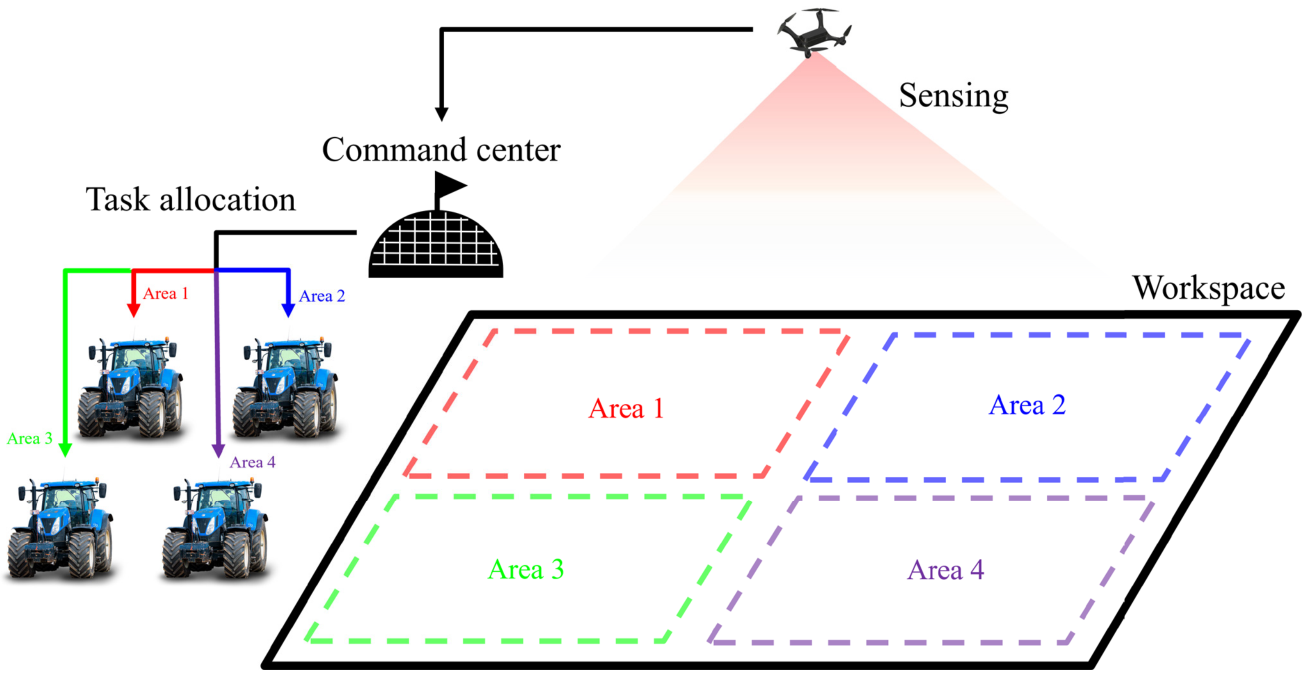


FIGURE 1. **Task allocation system for autonomous tractor fleet: A camera-equipped UAV detects the workspace and calculates and allocates a suitable sub-workspace to each tractor.**

workload distribution that is as balanced as possible to avoid robot overload or excessive idleness [19] due to performance variability of vehicles and unpredictable environmental conditions. Differences in engine power, fuel efficiency, payload capacity, and initial positioning significantly influence tractor performance, leading to uneven task completion times, resource underutilization, and operational challenges. Traditional task allocation methods often fail to address these variations adequately, resulting in productivity losses and suboptimal fleet performance. Thus, MRTA strategies become essential to mitigating these problems, ensuring that tasks are optimally allocated to match the capabilities and state of each vehicle.

To effectively address these challenges, tasks must be allocated by explicitly considering the performance and state variability of heterogeneous tractors. In a previous study [43], [44], we has extensively explored various MRTA techniques, focusing predominantly on spatial allocation methods such as Voronoi-based workspace partitioning (Fig. 1). Such methods leverage the Voronoi algorithm to partition workspaces, enabling MRS to receive distinct workspaces. This approach allows for dynamic allocation by incorporating robot-specific performance metrics and operational states. By assigning weighted values to each robot based on its capabilities such as distance from initial position, velocity, and battery capacity the method achieves differentiated partitioning, ensuring that each robot is allocated a task region proportional to its efficiency and capacity. However, these methods fail to account for how factors such as distance from the initial position, velocity, and battery capacity influence task duration, leading to suboptimal task allocation that does not guarantee the most efficient workspace distribution.

Therefore, an optimization process that explicitly considers the effect of these factors on the task completion time is necessary to achieve a more precise and effective allocation strategy. Incorporating critical influencing factors, including distance, velocity, and battery capacity, is crucial to achieve this result in workspace partitioning. In this study, we considered three key performance and state factors—distance, velocity, and battery capacity—to model task completion times. This task was performed on flat, unpaved terrain and assumed a path plan that followed the work nodes. The tractor's turning radius was set to a semi-circle with a diameter of 1m, based on the distance between the task nodes. Furthermore, we assumed that the tractor would recharge and re-enter the field after exhausting its battery capacity, thereby verifying the effectiveness of continuous charging. The allocation of workspaces considers the duration of simultaneous tasks, leading to efficient, equitable, and adaptive workspace partitions responsive to real-time operational data and environmental conditions. This synchronized approach enhances the scalability, adaptability, and overall operational efficiency of autonomous tractor fleets, providing a suitable, robust solution for dynamic agricultural environments.

III. VORONOI-BASED ISOTEMPORAL TASK ALLOCATION SYSTEM

This section presents the proposed task allocation system, integrating adaptive workspace partitioning and isotemporal

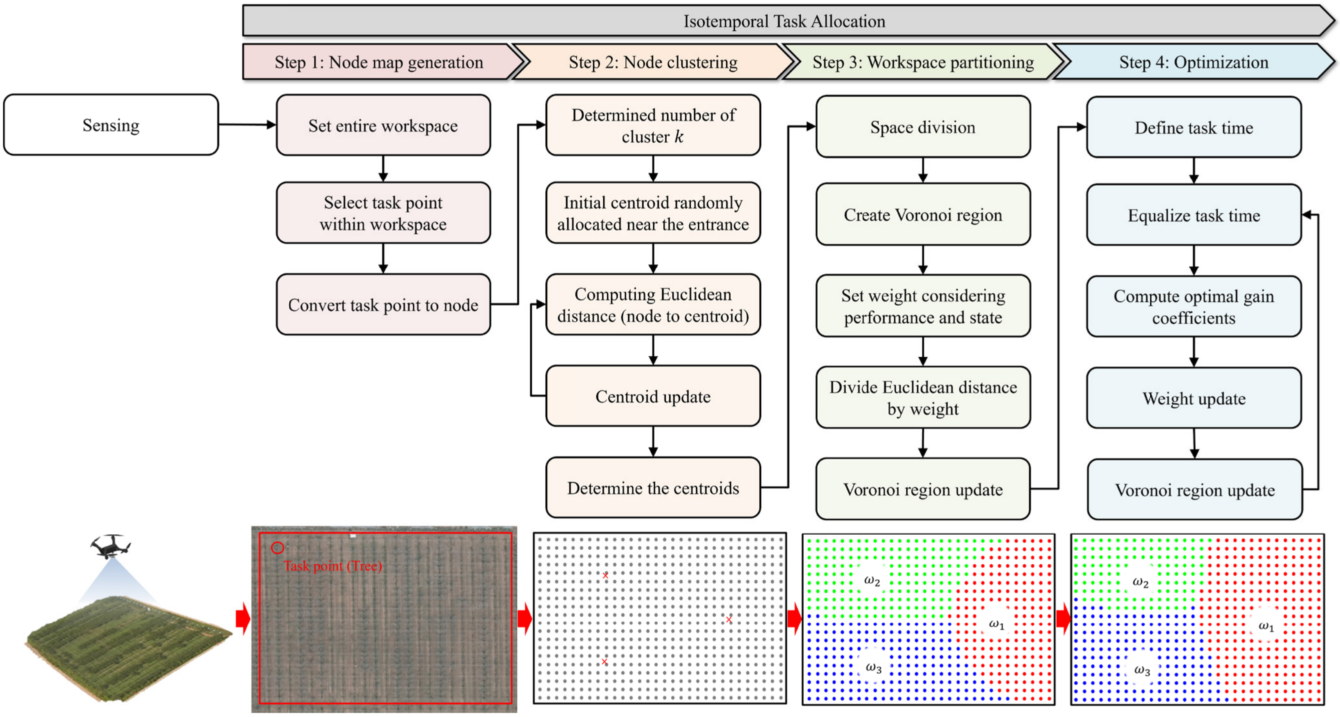


FIGURE 2. Flow chart of the proposed task allocation system.

optimization to enhance scalability, adaptability, and efficiency in multi-robot task execution. The isotemporal task allocation strategy ensures synchronized task completion across heterogeneous autonomous tractors by incorporating k-means clustering for the initial task grouping, weighted Voronoi diagrams for workspace partitioning, and isotemporal optimization techniques to adjust workload distributions dynamically. The proposed method accounts for variations in tractor performance metrics, including velocity, energy consumption, and payload capacity, ensuring that each tractor is allocated an optimized workspace based on its capabilities. Fig. 2 illustrates the process flow of the Voronoi-based isotemporal task allocation system, detailing the steps involved in node map generation, workspace partitioning, and isotemporal optimization.

A. NODE MAP GENERATION

Accurately mapping the agricultural environment is a fundamental requirement for precise task allocation and workspace partitioning in autonomous tractor systems. Thus, UAV-based photogrammetry was adopted as computationally efficient approach for workspace mapping to mitigate these constraints [49]. Using UAV equipped with mapping camera, ensuring comprehensive field coverage with minimal operational cost.

As shown in Fig. 3, the mapping process begins with aerial sensing to detect and classify task-relevant areas. The collected spatial data are processed to extract task points, which are discretized as individual nodes in the workspace. Each task point is systematically converted into a corresponding node on the generated node map, capturing spatial dependencies and functional constraints for efficient task execution. This structured workspace representation provides the foundation for isotemporal task allocation by incorporating terrain topology, crop distribution, and field accessibility constraints. Integrating UAV-based mapping

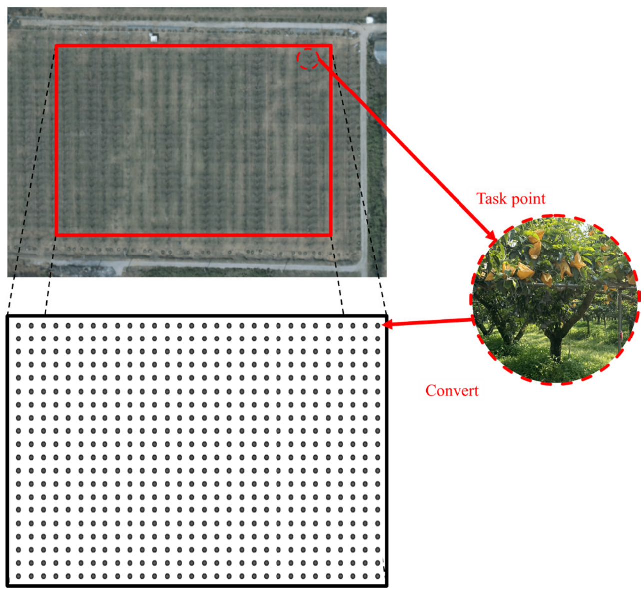


FIGURE 3. Generation a sensing image based node map using UAV with camera.

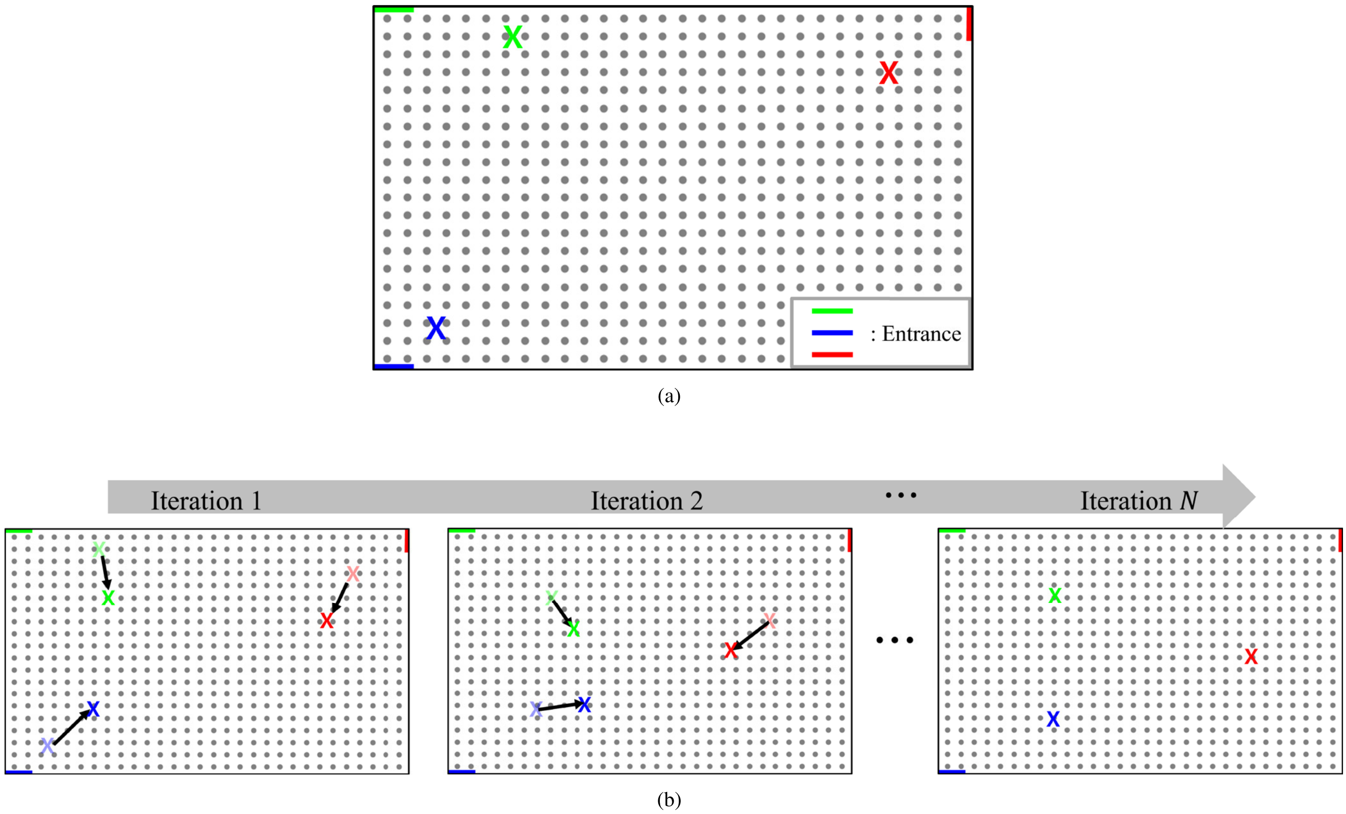


FIGURE 4. **Node clustering using *k*-means clustering algorithm: (a) Initial centroid placed in an arbitrary space close to the entrance, (b) Calculation process until the center point of the sub-workplace no longer changes.**

accelerates initial data acquisition and enhances the scalability and adaptability of task allocation methods, supporting the deployment of autonomous tractors in large-scale and dynamically changing agricultural environments. This mapping pipeline forms a critical component of the proposed system, enabling optimized and context-aware workspace partitioning for autonomous field operations.

B. WORKSPACE PARTITIONING

1) NODE CLUSTERING

The first step in workspace partitioning involves node clustering, identifying the central points for partitioning the workspace using a Voronoi diagram. This process establishes cluster centroids to allocate workspace among k autonomous tractors. The initial cluster centroids are strategically placed near the current positions of the tractors to enhance the efficiency and effectiveness of task allocation. This approach minimizes initial travel distances, reduces energy consumption, and optimizes resource utilization. The k-means clustering algorithm, a well-established and computationally efficient method for partitioning high-dimensional data, is employed due to its effectiveness proven over several decades in clustering tasks [50].

The total set of task-relevant nodes is denoted as $R_n = x_i, (i = 1, 2, \ldots, n)$, representing spatially distributed task points in workspace R. Given R_n, the algorithm partitions these nodes into $C = c_j, (j = 1, 2, \ldots, k)$ clusters, where each cluster c_j has a centroid denoted by μ_j. The objective of k-means clustering is to minimize the total within-cluster sum of squared errors (SSE), defined as the squared Euclidean distance between each node x_i and its corresponding cluster centroid μ_j, as formulated in Eq. 1:

$$SSE(C) = \sum_{j=1}^{k} \sum_{x_i \in C_j} |x_i - \mu_j|^2 \tag{1}$$

where k represents the number of autonomous tractors for the agricultural task. The k-means clustering algorithm proceeds through a structured iterative process, as illustrated in Fig. 4. First, an initial centroid μ_j^1 is randomly selected for each cluster, serving as the initial cluster center point p_{cc} near the entrance. Second, all nodes are allocated to the nearest p_{cc}. Third, the updated position of each p_{cc} is calculated based on the centroid for all allocated nodes in the cluster. Finally, this process is repeated for N times or until convergence, defined as the point where no further change in any p_{cc} occurs, as formulated in Eq. 2:

$$p_{cc} = \mu_j^{(N+1)} = \frac{1}{|C_j^{(N)}|} \sum_{x_i \in C_j^{(N)}} x_i \tag{2}$$

By systematically clustering task nodes R_n into k groups, the system derives optimal cluster centroids for

Voronoi-based workspace allocation. Combined with strategic centroid initialization near tractors, this approach ensures balanced workloads, minimizes tractor idle time, and enhances task execution efficiency. Consequently, the proposed clustering method supports scalable and adaptive workspace partitioning, facilitating robust and efficient operations in dynamic agricultural environments.

2) VORONOI-BASED PARTITIONING

The second step for workspace partitioning is the Voronoi-based partitioning process, which partitions areas based on p_{cc}. The Voronoi diagram algorithm is applied using the determined p_{cc} to partition the entire R into k sub-workspaces. The Voronoi diagram is a geometric structure that partitions a specific space into areas based on proximity, where each point in the area is closest to a center point compared to any other point [51]. This structure ensures that the workspace is partitioned equitably based on the spatial distribution of task points, enabling efficient and balanced task allocation. In detail, the point p_{cc_i} in R is represented as $X_i = (x_i, y_i)$. In addition, let p denotes a random position in the R space, represented as $X = (x, y)$. The set of non- overlapping areas on the R space is defined as $G = (p_{cc_1}, p_{cc_2}, \ldots, p_{cc_k})$, where each area corresponds to the area closest to a p_{cc_i}. The Euclidean distance between a point p and p_{cc_i}, is given by $d(p, p_{cc_i})$, as defined by Eq. 3:

$$d(p, p_{cc_i}) = \|X - X_i\| \tag{3}$$

where, the Voronoi diagram area$V(p_{cc_i})$ is defined by Eq. 4 as follows:

$$V(p_{cc_i}) = \{d(p, p_{cc_i}) \leq d(p, p_{cc_j}), \forall j \neq i\} \tag{4}$$

Considering the unique performance and state of each tractor, dividing the workspace is essential for efficient task allocation. Considering these factors, a positive weight is calculated that reflects the performance and state of each robot. This weight, denoted by ω_i, is employed to influence the workspace partitioning process, ensuring that task allocation is tailored to the capabilities and operational conditions of each tractor. The variable ω_i is defined by Eq. 5 as follows:

$$\omega_i = \sigma\omega_i^d + \varphi\omega_i^{mv} + \zeta\omega_i^c \tag{5}$$

where ω_i is calculated considering three critical performance and state of the tractor: the distance to the task starting point ω_i^d, the tractor velocity ω_i^{mv}, and the tractor fuel capacity ω_i^c. In addition, σ, φ, ζ are gain coefficients g_c, representing the relative importance of the performance and state and allowing the system to consider the effects on task performance. However, in this case, all g_c values were set to 1, treating the weight as equally weighted. These factors are integral to defining ω_i because they collectively represent the ability of the tractor to perform tasks efficiently in its allocated workspace. The three factors are defined by Eqs. 6, 7, and 8 as follows:

$$\omega_i^d = 1 - \frac{d_i}{\sum_{i=1}^{n} d_i} \tag{6}$$

$$\omega_i^{mv} = \frac{mv_i}{\sum_{i=1}^{n} mv_i} \tag{7}$$

$$\omega_i^c = \frac{c_i}{\sum_{i=1}^{n} c_i} \tag{8}$$

where d_i represents the distance from the initial robot position to a task starting point, mv_i denotes the maximum robot velocity, and c_i indicates the fuel or battery capacity of the robot. The weighting distance for applying such a weight is defined in Eq. 9 as follows:

$$d_W(p, p_{cc_i}) = \frac{1}{\omega_i}\|X - X_i\|, \omega_i > 0 \tag{9}$$

Therefore, the i-th sub-workspace W_i allocated to the i-th tractor is equal to the weighted Voronoi region $V_W(p_{cc_i})$, which is defined in Eq. 10 as follows:

$$W_i = V_W(p_{cc_i}) = \{d_W(p, p_{cc_i}) \leq d_W(p, p_{cc_j}), \forall j \neq i\} \tag{10}$$

C. ISOTEMPORAL TASK ALLOCATION

The isotemporal task allocation process optimizes task distribution by dynamically adjusting g_c to achieve synchronized task completion across all tractors. In the previous step, workspace partitioning was performed, assuming that the performance and state of each tractor contributed equally to task allocation, with identical g_c values applied uniformly. However, this assumption does not accurately capture the varying effects of the critical performance and state factors, such as the distance from the starting point of the task, velocity, and fuel capacity, on task completion time. These variations result in unbalanced workloads, causing inefficient overall system performance. The isotemporal task allocation process introduces adaptive g_c, systematically optimized to regulate the weighting of these primary performance metrics to address this challenge. The parameters σ, φ, and ζ modulate the influence of ω_i^d, ω_i^{mv}, and ω_i^c, respectively. By dynamically adjusting these coefficients, the system equalizes the estimated task completion times across all tractors, preventing any single tractor from overloading or underutilization.

This study establishes a mathematical framework that minimizes deviations in task completion times T_i among tractors to quantify the effectiveness of isotemporal task allocation. The objective function is formulated to minimize the deviation s_d of T_i, ensuring synchronized execution across all tractors. The deviation metric, s_d, measures the dispersion of individual tractor T_i from the mean task completion time, indicating the imbalance in workload distribution. A lower s_d value corresponds to a more evenly distributed workload across the fleet, preventing excessive delays caused by underperforming tractors while optimizing resource use. This metric is defined by Eq. 11 as follows:

$$s_d = \sqrt{\frac{\sum_{i=1}^{k}(T_i - \overline{T})^2}{k}} \tag{11}$$

where $\overline{T}$ represents the mean task completion time for all tractors, serving as the reference task duration for equalized T_i. This factor is crucial for identifying whether the workload is balanced across all tractors and preventing scenarios in which a subset of tractors completes the tasks significantly earlier or later than others. $\overline{T}$ is defined using Eq. 12 as follows:

$$\overline{T} = \frac{1}{k}\sum_{i=1}^{k} T_i \tag{12}$$

The optimization problem is formulated to determine the optimal gain coefficients g_{opti} that minimize s_d, ensuring balanced T_i across all tractors. The gain coefficients directly influence how the workload is redistributed dynamically to achieve synchronization in T_i. The optimization is defined using Eq. 13 as follows:

$$g_{opti} = \arg\min_{g_c} s_d(g_c) \tag{13}$$

The estimated task time T_i for each tractor is defined using Eq. 15 as follows:

$$T_i = T_{work} + T_{battery} + T_{travel} \tag{14}$$

$$= T_{W_i} + \frac{T_c}{e_i \zeta \omega_i^c} + \sigma \omega_i^d \varphi \omega_i^{mv} \tag{15}$$

where T_{work} represents the time for a tractor to complete its designated task. This factor is influenced by the spatial characteristics of the allocated region and the movement efficiency of the tractor. In addition, $T_{battery}$ accounts for the time for refueling or recharging. This term is inversely proportional to e_i, the energy consumption efficiency, representing the fuel efficiency and storage capacity of the tractor. Moreover, T_{travel} represents the influence of the travel time on task completion. The coefficients σ and φ regulate the effects of ω_i^d and ω_i^{mv} in determining the overall T_i. The equation comprehensively represents the factors affecting task duration by explicitly modeling these components.

As shown in Algorithm 1, isotemporal task allocation involves iteratively improving the gain coefficients to minimize the task time variance across the fleet. The $\Delta s_d < \epsilon$ indicates that the s_d is sufficiently minimized, and adjustments to g_c are iteratively performed until the s_d is minimized as much as possible. As explained in Section III-B2, g_c represents a gain coefficient of the weights that quantifies the relative importance of each performance and state weight (ω_i^d, ω_i^{mv}, and ω_i^c) in determining the effective operating performance ω_i of each tractor. Consequently, changes in g_c directly affect the workload allocation by adjusting the expected task completion time T_i of each tractor. The system dynamically optimizes these factors to repeatedly redistribute the workload across the entire autonomous tractor fleet, ensuring that task execution times are minimized and workloads are balanced.

Algorithm 1 Isotemporal Task Allocation

Input: Pre-allocated workspace $W = \{W_1, \ldots, W_k\}$ for tractors, initial gain coefficient $g_c = \{\sigma, \phi, \zeta\}$
Output: Optimal gain coefficients g_c^*

```
Initialize g_c
repeat
    for each tractor with allocated workspace W_i ∈ W do
        Compute ω_i ← g_c · [ω_i^d, ω_i^mv, ω_i^c]
        Compute task time T_i ← (W_i, ω_i)
    end for
    Compute standard deviation s_d ← std({T_1, ..., T_k})
    if s_d^new < s_d then
        s_d ← s_d^new
        g_c ← g_c^new
    else
        continue
    end if
until Δs_d < ε
```

IV. EXPERIMENTAL DESIGN

A. EXPERIMENTAL SETUP

The experiment used the agricultural environment of Chonnam National University as shown in Fig. 5. The experiment was focused on the seeding system. As shown in Fig. 5(a), the entire workspace was set to $651m^2$ ($31m \times 21m$). The task points within the area were set to the same row and column spacing of 1m, and a total of 600 task points were set. As shown in Fig. 5(b), the UAV used in the experiment was a quadcopter-type drone (3DR SOLO) equipped with an RGB camera. The camera for image acquisition used a GoPro Hero 4 model with a resolution of 3840×2160. The UAV acquired images of the agricultural environment at an altitude of 70m. Since the actual tractor platform has experimental limitations due to hardware and environmental factors, this study only verified the performance of the proposed system by applying it to a mobile robot platform. The number of robots when partitioning the workspace was set to 3 robots that were actually available. Each UGV performed the task by allocating the partitioned workspace calculated through the proposed algorithm on a laptop to each mini-computer.

The parameter settings of the UGV were set as shown in Table 1. The parameters were set to the distance to the task start point d_i, velocity mv_i, battery capacity c_i, as well as the task time per node T_{ω_i}, battery consumption rate e_i, and battery recharging time T_c. It takes T_{ω_i} time for each robot to complete the sowing task on one node, and the battery capacity of each robot is consumed as much as e_i while performing the task. In addition, when the battery is completely consumed while the robot performs the task, it consumes T_c battery charging time and performs the task

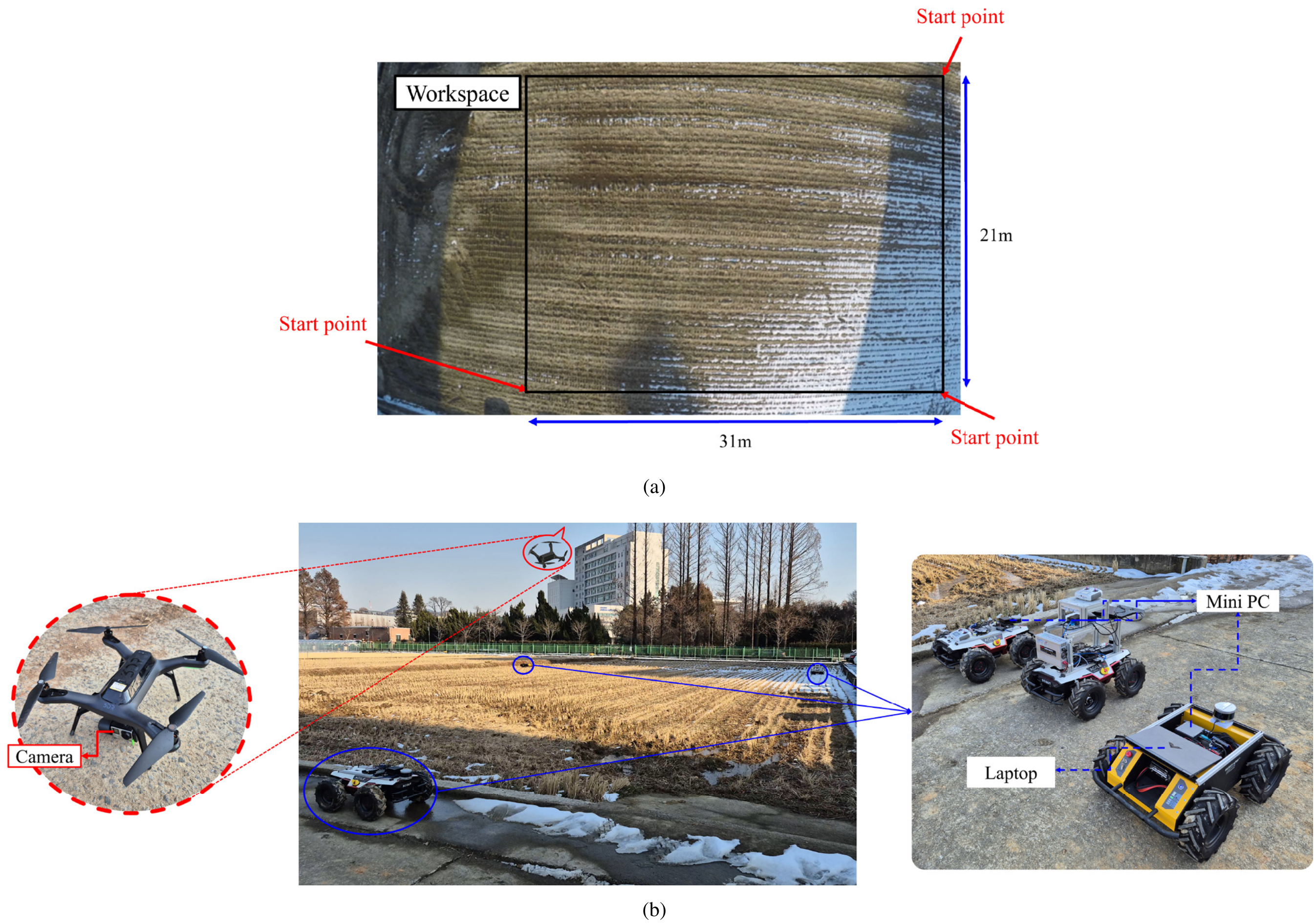


FIGURE 5. Experimental setup for evaluation: (a) Top view image of experimental environment, (b) Overall experimental environment and configuration.

TABLE 1. Experimental parameters of heterogeneous robots.

Robot	d_i	ω_i^d	mv_i	ω_i^{mv}	c_i	ω_i^c	T_{ω_i}	e_i	T_c
r_1 (Scout 1)	15	0.30	2	0.45	20	0.14	8	0.09	
r_2 (Scout 2)	5	0.76	1	0.22	75	0.52	12	0.12	60
r_3 (Husky)	1.5	0.96	1.5	0.33	50	0.34	10	0.1	

again after charging is complete. The experiments were conducted for both non-optimized ($\sigma = \varphi = \zeta$) and optimized ($\sigma \neq \varphi \neq \zeta$) cases to evaluate the optimization workspace of the proposed algorithm. Each UGV is driven through a headland pattern using the one-way method, which is a conventional tractor driving method in [52].

The experiments were conducted to evaluate the scalability, adaptability, and efficiency of the proposed algorithm through numerical verification and field evaluation. Both evaluations are performed based on images acquired through UAV in the same environment. The numerical validation is performed to verify the smooth applicability to field experiments and the scalability to various models (platforms). The field evaluation is performed to verify the applicability and efficiency of the proposed algorithm by applying it to real environments and robots based on the numerical validation results.

B. PERFORMANCE METRICS

We used three performance metrics to evaluate the proposed isotemporal task allocation system. The performance metrics are the number of nodes allocated per robot N_i, the total task time T_{total}, and the cumulative task time T_{cum}. These key performance metrics are designed to quantitatively evaluate the workload balancing and task execution efficiency.

The metric N_i is employed to verify that task allocation is proportionally distributed based on the performance capabilities and operational states of each robot, ensuring an equitable workload distribution. This metric is formally defined as follows:

$$N_i = \sum p^i_{allocated} \tag{16}$$

where $p^i_{allocated}$ represents task nodes allocated to the i-th sub-workspace. This metric quantitatively evaluates the workload allocated through the workspace partitioning. The difference in N_i between robots represents the workload balancing allocated to each robot, and robots with higher performance, such as task processing efficiency, are allocated more tasks for a balanced workload.

The metric T_{total} quantifies the maximum time it takes for a robot to complete an allocated task, effectively measuring the efficiency of the proposed system performance. This metric is defined as follows:

$$T_{total} = \max(T_1, T_2, \ldots, T_i) \tag{17}$$

where T_i denotes the task completion time of the i-th robot. Since T_{total} is defined as the latest task completion time among all robots, it is an important indicator to determine whether the proposed task allocation algorithm optimally distributes the workload allocated to each robot. The lower the value of T_{total}, the better the performance of the proposed system, and minimizing the value of T_{total} ensures optimal workload distribution.

The metric T_{cum} measures the overall system workload by summing the task completion times of each robot. T_{cum} can be used to evaluate the balancing of task distribution and resource allocation efficiency for all robots. This metric is formally defined as follows:

$$T_{cum} = \sum_{i=1}^{k} T_i \tag{18}$$

where T_{cum} is defined as the sum of the task times of all robots. A lower value of T_{cum} indicates higher task efficiency. However, it is difficult to evaluate the task distribution balancing of the proposed system with only the value of T_{cum}, so it is evaluated through the standard deviation of the task time. A lower standard deviation indicates a more balanced workload distribution. In addition, the task time ratio represented by T_{cum} is evaluated in terms of how proportionally the workload is distributed among the robots. Considering these factors comprehensively, it directly reflects the ability of the system to achieve balanced workload distribution, and can effectively evaluate the performance of the proposed algorithm.

V. EXPERIMENTAL RESULTS

To evaluate the performance of the proposed system, numerical validation and field evaluation were performed. This evaluation evaluated the effectiveness of the isotemporal task allocation strategy in optimizing task execution and workload distribution in an autonomous robot fleet. By maintaining consistency in experimental parameters, the adaptability, scalability, and efficiency of the proposed method were verified by directly comparing the simulated performance with the actual performance.

TABLE 2. The results of isotemporal task allocation parameters.

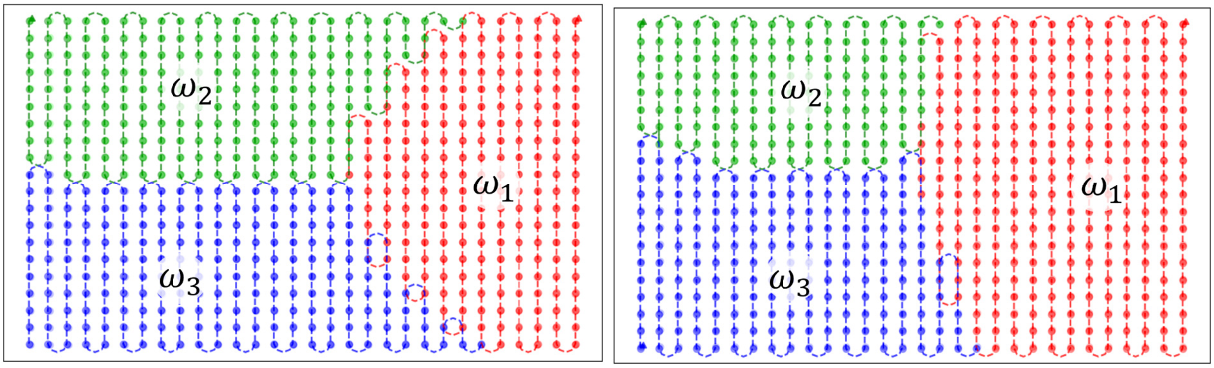
Parameter	σ	φ	ζ	ω_1	ω_2	ω_3
Non-optimized	$0.3\dot{3}$	$0.3\dot{3}$	$0.3\dot{3}$	0.30	0.50	0.53
Optimized	0.19	0.78	0.03	0.41	0.33	0.44

The results of the isotemporal task allocation are shown in Table 2. These results were derived through an optimization procedure that iteratively adjusted gain factors based on given performance data to minimize total operation time. In the experimental setup, the relatively small workspace compared to real-world environments reduced the contribution of fuel and battery factors, while velocity contributed most by directly reducing movement and operation times in sub-workspaces. Through the optimized gain coefficients, the gain coefficients for fuel and battery capacity showed the lowest values, which means that fuel and battery capacity had the least influence on the task time. On the other hand, the gain coefficient values for velocity showed the highest values, which shows that the velocity had the greatest influence on the task time.

A. NUMERICAL VALIDATION

We performed numerical validations to evaluate the performance, scalability, and stability of the proposed isotemporal task allocation system in simulations based on real environments. The numerical verification has been performed previously in our previous work [53], and this subsection reviews the results. We evaluated the performance of the proposed system by optimizing the workspace partitioning and balancing the workload distribution in a heterogeneous autonomous robot fleet using the proposed method. As shown in Fig. 6, we compare the optimized and non-optimized cases to confirm that the gain factor plays an important role in improving the overall system efficiency, and we verify the scalability and stability of the proposed isotemporal task allocation system. Each color (red, green, and blue) represents the workspaces allocated to robots r_1, r_2, and r_3, respectively. Furthermore, the dotted lines in Fig. 6 represent the actual paths traveled by each robot in the simulation. Although some paths overlapped due to the tractor's driving characteristics, the simulation confirmed smooth operation without collisions.

As shown in Table 3, r_1 is allocated the most nodes, while r_2 is allocated the least task nodes. This means that r_1 has the highest performance among the three robots, while r_2 has the lowest performance. The T_{total} of the proposed system is reduced by 29.82%. This reduction indicates that

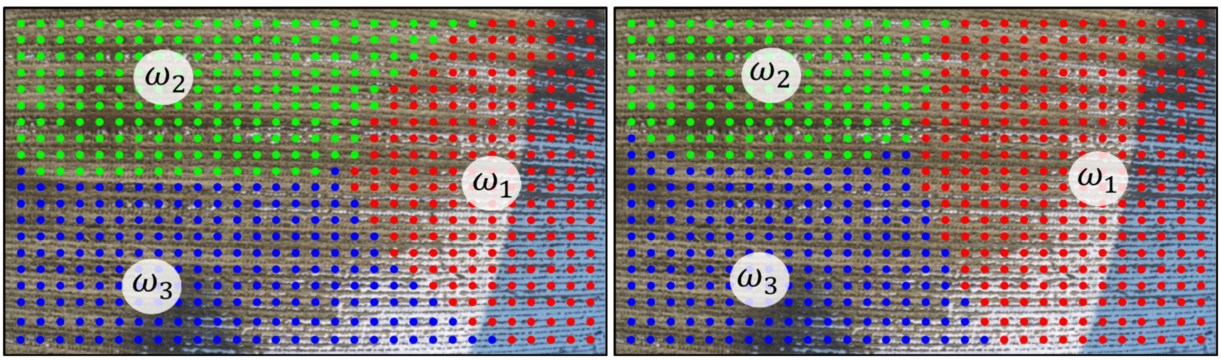


(a) (b)

FIGURE 6. Comparsion of numerical validation for the proposed system performance: (a) Non-optimized isotemporal task allocation in numerical simulation, (b) Optimized isotemporal task allocation in numerical simulation.

TABLE 3. Experimental results of the numerical validation.

Environment	Case	Robot	$N_i(n)$	$T_i(s)$	$T_{total}(s)$	$T_{cum}(s)$	s_d
Simulation	Non-optimized	r_1	205	2,003.21	4,045.27	9,006.32	836.87
		r_2	193	4,045.27			
		r_3	202	2,957.84			
	Optimized	r_1	276	2,733.92	2,843.56	8,305.32	53.18
		r_2	134	2,843.56			
		r_3	190	2,727.84			



(a) (b)

FIGURE 7. Comparsion of field evaluation for the proposed system performance: (a) Non-optimized isotemporal task allocation in real environment, (b) Optimized isotemporal task allocation in real environment.

TABLE 4. Experimental results in open field environment.

Environment	Case	Robot	$N_i(n)$	$T_i(s)$	$T_{total}(s)$	$T_{cum}(s)$	s_d
Open Field	Non-optimized	r_1	202	2,224.92	4,144.14	9,525.79	783.65
		r_2	194	4,144.14			
		r_3	204	3,156.74			
	Optimized	r_1	275	2,936.14	3,071.71	8,970.95	55.67
		r_2	135	3,017.10			
		r_3	190	3,071.71			

the proposed isotemporal task allocation scheme improves the cooperative task of the fleet system by minimizing the task time difference between the robots. The T_{cum} of the proposed system is reduced by 7.78%, which indicates that the proposed method improves the workload balance to some extent. This result may mean that the performance of the proposed system is not very good, but as mentioned earlier, this indicator should consider additional factors. As shown in the results of previous studies [53], the slope of the T_{cum} graph in the optimized scenario is more constant and linear than that in the non-optimized case. Specifically, the proposed system showed a 93.65% reduction in s_d. This result means that the proposed task allocation system minimized the difference in task completion times of all robots. The consistency of each task time indicates that the proposed system distributed the task time more evenly among all robots, preventing unnecessary time waste by allowing some robots to complete the task faster than others.

The results of numerical validation showed that the proposed system efficiently performed tasks by allocating appropriate workloads to robots with different performances and states and minimizing unnecessary task time. In the non-optimized case, the workspace was partitioned differentially, but it caused a lot of unnecessary waiting time until the highest performing robot completed all tasks and the lowest performing robot completed them. Numerically, the highest performing robot had to wait for the remaining time after performing the same task again. However, in the optimized case, all task times were performed within 2 minutes, minimizing unnecessary waiting time. These results of numerical validation showed that the proposed system can be applied to various platforms and can perform tasks efficiently.

B. FIELD EVALUATION

We conducted a field evaluation to evaluate the performance, reliability, and adaptability of the proposed isotemporal task allocation algorithm in a real agricultural environment. The field evaluation evaluated the proposed system adaptability in a real agricultural environment and the reliability that was not different from the numerical verification results. As shown in Fig. 7, similar to the numerical validation, we verified the performance of the proposed system in terms of workload distribution and system adaptability through comparative analysis of the non-optimized and optimized cases. Similar to Figure 6, each color (red, green, and blue) represents the workspaces allocated to robots r_1, r_2, and r_3, respectively. Although the robots' movement paths are not separately displayed in Fig. 7, the simulation results were similar to those in Fig. 6, confirming that all robots moved stably and without collisions.

The results of the field evaluation are presented in Table 4, which are similar to the results of the numerical verification. It shows that the most nodes are allocated to the best performing r_1, and the least nodes are allocated to the worst performing r_2. In the optimized case, we confirmed the effect of the gain factor, which significantly minimizes the difference in task time and equalizes the task completion times of all robots. T_{total} also shows a significant reduction. In the optimized case, T_{total} is reduced by about 25.88%. In addition, T_{cum} is reduced by 5.82%, and s_d is significantly reduced by 92.89%. This indicates that the proposed system's workspace partitioning effectively integrates important performance indicators such as velocity, battery capacity, and initial positioning in a real environment, thereby ensuring a balanced workload distribution among robots with different performances and states.

The numerical verification and field evaluation of the proposed system under the same conditions showed similar results. The N_i showed very minor differences, and the T_{total} showed relative errors of 2.39% and 7.43% for each case. Similarly, the T_{cum} showed relative errors of 5.45% and 7.42% for each case, and the s_d showed relative errors of 6.36% and 0.04% for each case. These results demonstrate that the proposed system maintains high consistency and performance in real environments and numerical simulations. Therefore, it can be directly applied to real environments and platforms through realistic environment and platform based simulations, and can show stable and high accuracy. Through these experiments, we demonstrate the practical applicability of the proposed system to real agricultural environments and platforms, and highlight its potential to enhance the scalability, adaptability, and efficiency of MRS in precision agriculture.

VI. DISCUSSION

A. NODE MAP GENERATION

The proposed system is designed to be scalable to various tasks. In this study, we applied the proposed system to the sowing system and conducted experiments. However, not all tasks can set up and perform these experimental environments in the same way. In particular, in the orchard environment, the task points are trees during harvesting or spraying task. However, it is still difficult to apply because trees act as obstacles rather than task points during driving. Nevertheless, the proposed system can be applied in other ways. For example, in the case of spraying task, data can be provided in an environment suitable for generating paths between nodes through node map generation. Therefore, by integrating the node map generation research applicable to each agricultural task, widely applicable task allocation can be performed.

B. PATH PLANNING

The proposed system has been proven through experiments to perform optimal tasks. Multi-UGV are allocated to task nodes and simply follow them. This method should consider the path through the dynamic structure of the platform, especially the tractor, for the rotation to move to the next row or column. For the robots (scout, husky) used in this study, path planning for tractor rotation is not required. However, for application to actual tractors, task allocation studies including path planning considering the structure of the platform are required. Additionally, because the terrain where work is performed in agriculture is an unstructured environment, a path planning algorithm that takes into account factors such as traversability is required. An autonomous tractor fleet system that integrates these studies will be able to perform more optimal agricultural tasks.

C. PERFMANCE AND STATE PARAMETER SETTING

The proposed task allocation system is implemented by considering the platform performance and current state. However, in the actual tasking environment, there are many parameters that need to be considered for the tractor and the surrounding environment. In order to achieve optimal task allocation, all parameters must be considered for task distribution. In addition, other parameter settings are required depending on the environment. Furthermore, the addition of multiple variables can lead to weight calculation distortions due to differences in units and ranges. To address this issue, additional normalization techniques are required to calculate weights. This approach can perform appropriate task allocation for various environments and platforms.

D. DIRECTIONS FOR FUTURE WORK

The insights gained from this study suggest several avenues for advancing agricultural robotic systems. The proposed concurrent task allocation algorithm is generalizable and can be applied to a wider range of contexts. Despite adopting simple parameters, this study demonstrates that the proposed algorithm can be effectively applied to heterogeneous swarm tractor or robot control. Future research can aim to develop quantitative performance metrics for practical validation by evaluating parameters for real-world platforms and terrains, task completion efficiency, precision through repeated experiments, performance superiority through comparisons with other task allocation algorithms, and adaptability to diverse environments and tasks.

Performance validation in large-scale robot fleets and extensive experimental environments is crucial to ensuring the scalability and robustness of the proposed algorithm. Furthermore, the addition of metrics that affect performance and state parameter settings in real-world tasks plays a crucial role in verifying the performance of the proposed algorithm more clearly. Developing systematic normalization or scaling methods for these heterogeneous metrics will improve the interpretability and consistency of multi-robot task allocation. Performance evaluations will expand beyond the current metrics and allow for a more comprehensive evaluation through comparisons with other task allocation algorithms. By addressing these limitations, future research could improve the robustness, scalability, and practical applicability of the proposed approach to real-world agricultural robot fleets.

VII. CONCLUSION

This study proposes a Voronoi-based isotemporal task allocation system for autonomous tractor fleet. It is designed to derive optimal weights by reflecting the performance and state importance of each robot and efficiently partition the workspace. Performance and state are evaluated based on parameters such as distance, velocity, and capacity, including the number of allocated nodes, total work time, and accumulated work time. Comparing the pre- and post-optimization results, we confirmed that equalizing work times can reduce waiting times and improve agricultural work efficiency. Furthermore, numerical validation and field evaluations demonstrate the applicability and practical utility of the proposed algorithm. These results demonstrate its potential for extension to various tractor-based collaborative work models.

In the future, we would like to extend the current research to more complex and various scenarios. The currently proposed algorithm is designed for a simple scenario without obstacles. Considering the influence of the surrounding environment and obstacles in the task allocation algorithm is one of our main research tasks. Therefore, the proposed task allocation algorithm can be further integrated with SLAM and path planning algorithms to perform an improved task allocation system for autonomous tractor fleet systems.

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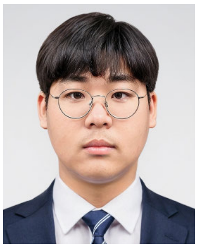

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