A Hybrid ACO-DWA and Distributed Task Allocation Framework for Efficient Multi-Robot Operations in Unstructured Agricultural Environments

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The deployment of multiple autonomous robots in agricultural operations offers significant potential for improving efficiency, reducing labor costs, and enhancing sustainability. However, navigating unstructured farm environments while coordinating multiple robots presents challenges such as collision avoidance, dynamic obstacle management, and efficient task allocation. This study proposes a novel framework that integrates a hybrid Ant Colony Optimization (ACO) and Dynamic Window Approach (DWA) for global path planning with a distributed priority-based task allocation strategy. The ACO-DWA hybrid optimizes global trajectories while ensuring smooth and dynamically feasible paths, whereas the distributed priority-based mechanism enables conflict-free coordination and balanced task distribution among multiple robots. Extensive simulations and ROS-based experiments were conducted in 2.5D grid-based farm environments with varying terrain, obstacles, and robot densities. Results indicate that the proposed framework outperforms conventional algorithms in terms of path length, energy consumption, task completion time, and collision avoidance. Scalability analysis demonstrates the framework's ability to maintain high performance with increasing robot team sizes. Overall, the proposed methodology provides a robust, efficient, and scalable solution for autonomous multi-robot operations in complex agricultural settings, with potential applications in harvesting, monitoring, and precision farming.

Keywords: Autonomous Robots, Agricultural Operations, Multi-Robot Coordination, Ant Colony Optimization (ACO), Dynamic Window Approach (DWA), Path Planning

Introduction:

Multi-robot systems (MRS) have emerged as a transformative technology in both industrial and agricultural domains, enabling the execution of complex tasks with enhanced efficiency, robustness, and scalability [1][2]. In agriculture, particularly, autonomous robots are increasingly deployed for tasks such as harvesting, weeding, spraying, and transportation, where human labor is either costly or inefficient [3]. Safflower, a crop with significant economic and pharmaceutical importance, presents challenges for manual harvesting due to its asynchronous maturation and environmental variability. Multi-robot deployment for safflower harvesting can improve productivity, reduce labor costs, and enable precise agricultural operations; however, this also introduces challenges in real-time decision-making, conflict resolution, and coordinated path planning in unstructured and dynamic environments[4]. Effective path planning is critical for ensuring task efficiency, minimizing redundant movements, and optimizing energy consumption, particularly in environments with irregular terrain, obstacles, and dense planting[5][6]. While single-robot path planning algorithms such as A*, Dijkstra's algorithm, Ant Colony Optimization (ACO), and Rapidly-Exploring Random Trees (RRT) have demonstrated efficacy in controlled settings, their direct application in unstructured farm environments is often inadequate[7][8]. Multi-robot path planning and task allocation introduce further complexity, requiring coordination strategies that balance efficiency, collision avoidance, and energy optimization[9]. Both centralized and distributed approaches have been explored, with centralized methods excelling in stable environments but suffering scalability issues, and distributed approaches providing adaptability and real-time responsiveness but requiring robust communication protocols[2] [10]. Therefore, there is a pressing need for advanced strategies that integrate path planning, task allocation, and conflict resolution tailored to multi-robot agricultural operations.

Research: Gap:

Despite significant advancements, several critical gaps persist in the field of multi-robot agricultural systems. First, existing research predominantly focuses on controlled or semi-structured environments, limiting the applicability of proposed algorithms to real-world farms with unstructured terrain, dynamic obstacles, and variable crop layouts [7][11].Second, while multi-robot path planning has been extensively studied, most approaches either optimize for a single metric, such as distance or energy consumption, or rely on centralized control architectures that cannot scale efficiently with increasing team size [10]. Third, conflict resolution among multiple robots operating in constrained or overlapping spaces remains inadequately addressed, particularly in distributed systems where real-time coordination is critical[10][12]. Finally, the integration of global and local path planning with dynamic task allocation in heterogeneous multi-robot teams is underexplored, especially in agricultural settings requiring collision-free, energy-efficient, and time-optimal operations. These gaps indicate the necessity of developing comprehensive frameworks that consider environment simulation, multi-objective optimization, and cooperative task management.

Objectives:

The primary objective of this research is to develop a robust and efficient multi-robot system framework for agricultural applications, specifically targeting safflower harvesting. The study aims to (1) design a 2.5D grid-based simulation model to represent unstructured agricultural environments; (2) implement an integrated path planning strategy combining Ant Colony Optimization (ACO) and Dynamic Window Approach (DWA) to generate distributed global and local paths for multiple robots; (3) develop a priority-based task allocation and conflict-resolution mechanism to prevent spatial overlap and optimize operational efficiency; and (4) validate the proposed framework through MATLAB and ROS simulations under realistic environmental and operational constraints. By addressing these objectives, the research seeks to enhance both the autonomy and efficiency of multi-robot agricultural operations.

Novelty Statement:

This study introduces a novel cross-regional scheduling and path planning methodology that simultaneously addresses multi-robot task allocation, collision avoidance, and environmental adaptability. Unlike prior approaches that focus on single-objective optimization or rely solely on centralized or distributed methods, the proposed framework integrates global and local path planning with a priority-based conflict-resolution strategy, enabling coordinated multi-robot operations in highly unstructured environments. The inclusion of a 2.5D environment simulation model allows realistic evaluation of robotic navigation under dynamic agricultural conditions, which has not been adequately addressed in prior research [9][13]. Additionally, the study leverages hybrid optimization techniques (ACO-DWA) to enhance both path efficiency and adaptability, making this framework a significant advancement over existing agricultural multi-robot planning systems.

Literature Review:

Multi-robot systems (MRS) have received extensive attention over the past two decades due to their potential to perform complex tasks cooperatively, with applications ranging from industrial automation to agriculture and disaster response[1][2]. Early research on multi-robot object transportation focused on centralized and behavior-based architectures. Parker (1998, 2000) introduced L-ALLIANCE, a distributed behavior-based framework that dynamically adjusts robot behaviors based on performance evaluation and environmental changes, validated through cooperative box-pushing tasks. Similarly, [8] proposed centralized task assignment and motion planning algorithms for multi-robot cooperative transportation in unknown static environments, which were later extended to three-dimensional environments. Other efforts, such as CAMPOUT[14],applied leader–follower decentralized strategies to validate multi-robot tasks in planetary exploration, highlighting the applicability of behavior-based distributed systems.

In agricultural robotics, multi-robot systems are increasingly deployed to improve efficiency, coverage, and precision in tasks such as harvesting, spraying, and monitoring [3][4]. Path planning is a crucial component in these systems. Single-robot global path planning methods, including A*, Dijkstra's algorithm, Ant Colony Optimization (ACO), and Rapidly-Exploring Random Trees (RRT), have been widely applied but often fail in unstructured and dynamic farm environments[7] [15]. To address these limitations, researchers have proposed hybrid methods that integrate machine learning and optimization techniques. For instance, [15] combined an enhanced A* algorithm with support vector machine regression to optimize orchard navigation, while [16]improved ACO for multi-objective path planning. Dynamic local path planning approaches, such as the Dynamic Window Approach (DWA), artificial potential fields (APF), and fuzzy logic-based methods, have been used to enable real-time trajectory adjustments in response to environmental changes[15][16]. Hybrid global-local strategies are increasingly recognized as necessary to balance efficiency, safety, and adaptability in unstructured agricultural environments.

Multi-robot path planning requires effective task allocation and coordination strategies. Centralized methods optimize operations using global information but may face scalability and computational bottlenecks as the number of robots increases [2]. Distributed methods, by contrast, provide greater autonomy to individual robots, enabling flexible responses to dynamic conditions but requiring robust inter-robot communication [11]. Recent work has explored distributed algorithms for collaborative harvesting, drone monitoring, and automated tillage operations. For example,[12]proposed a submap-based multi-robot exploration method integrating wavefront distance strategies, while[9] developed a steering-angle-based collision-free path planning approach optimizing both energy and task completion time.[13] Utilized a collaborative artificial bee colony algorithm for multi-robot task scheduling in smart farms, demonstrating enhanced efficiency in dynamic task allocation scenarios.

Another significant aspect of MRS research is multi-robot learning and adaptive behavior. [5][17] highlighted the importance of reinforcement learning (RL) and neural networks to improve cooperative strategies and system autonomy. In agriculture, integrating RL and optimization algorithms allows robots to adapt to changing environmental conditions, handle obstacles, and dynamically reallocate tasks to avoid collisions and ensure efficiency [15]. Recent studies emphasize the importance of combining behavior-based architectures with learning approaches to reduce the learning space and accelerate the development of autonomous multi-robot systems[17][18].

Despite these advances, challenges remain in developing MRS frameworks that simultaneously address dynamic path planning, conflict-free multi-robot scheduling, environmental adaptability, and operational efficiency. The integration of global and local path planning, distributed task allocation, and real-time conflict resolution for unstructured agricultural environments continues to be an active research frontier [9][13] [11]. Therefore, the development of hybrid and adaptive frameworks remains crucial for achieving fully autonomous, efficient, and scalable multi-robot agricultural systems.

Methodology:

The proposed methodology aims to develop an efficient multi-robot system framework for safflower harvesting, emphasizing path planning, task allocation, and conflict-free operation in unstructured agricultural environments. The methodology is structured into five main stages: environment modeling, global path planning, local path planning with conflict resolution, multi-robot task allocation, and system implementation and validation [5][19].

Environment Modeling:

A 2.5D grid-based simulation model is developed to represent the unstructured agricultural environment. Each grid cell encodes information about traversability, elevation, obstacles, and crop locations. Dynamic obstacles, including moving robots and human workers, are incorporated to simulate real-time operational conditions. This model forms the foundation for both path planning and task allocation, enabling the evaluation of multi-robot interactions and coordination under realistic farm scenarios.

Global Path Planning:

For global path planning, a hybrid algorithm combining Ant Colony Optimization (ACO) and the Dynamic Window Approach (DWA) is employed. The ACO algorithm simulates the pheromone-laying behavior of ants to generate near-optimal paths for each robot, considering multiple objectives such as path length, energy efficiency, and obstacle avoidance. The pheromone trails are updated iteratively based on the quality of paths, favoring trajectories that are shorter and safer. After candidate paths are generated by ACO, the DWA refines these paths by considering the robot's kinematic constraints and dynamic environmental information. Within a dynamic velocity window, the robot evaluates feasible movements and selects the trajectory that minimizes the distance to the goal while avoiding collisions. This hybrid approach ensures that global paths are both optimized and executable under realistic conditions.

Local Path Planning and Conflict Resolution:

Local path planning focuses on real-time adjustments to avoid dynamic obstacles and inter-robot collisions. The Dynamic Window Approach is used to continuously evaluate feasible velocities and adjust the robot's trajectory in response to changing conditions. To coordinate multiple robots operating in constrained spaces, a priority-based conflict resolution strategy is applied. Each robot is assigned a dynamic priority determined by factors such as task urgency, proximity to obstacles, and remaining energy. In situations of potential spatial overlap, lower-priority robots adapt their local paths to yield to higher-priority robots. This ensures collision-free operation while maintaining overall task efficiency and coordination.

Multi-Robot Task Allocation:

Task allocation is managed using a distributed priority-based scheduling algorithm. Each robot is assigned tasks according to its current position, capability, and workload. Spatial and temporal precedence constraints are applied to ensure coordination for interdependent tasks, such as sequential harvesting or the simultaneous transport of crop bundles. The task allocation algorithm continuously updates in real time to balance workloads among robots, minimize idle times, and prevent conflicts, while integrating with the global and local path planning strategies to maintain operational efficiency.

System Implementation and Validation:

The proposed framework is implemented using MATLAB for simulation and Robot Operating System (ROS) for multi-robot coordination and testing. MATLAB simulations allow evaluation under diverse environmental conditions, analyzing metrics such as path length, task completion time, energy consumption, and collision incidents. ROS-based testing enables real-time communication and coordination among multiple robots, validating the effectiveness of the hybrid ACO-DWA path planning and distributed task allocation strategies. Experimental scenarios include varying terrain slopes, obstacle densities, and team sizes to assess system robustness, scalability, and adaptability. Comparative analysis with conventional path planning and task allocation algorithms demonstrates the improvements in operational efficiency, safety, and coordination provided by the proposed methodology.

Pseudocode for Hybrid ACO-DWA Global Path Planning:

Input: Start position, Goal position, 2.5D grid environment
Output: Optimized, collision-free path
Initialize pheromone levels for all possible paths
For each iteration until maximum iterations:
For each robot:
Generate candidate paths based on pheromone levels and heuristic information
Evaluate paths using objective function (path length, energy, obstacles)
Select the best path probabilistically according to pheromone intensity
Update pheromone trails:
Evaporate pheromones on all paths
Deposit additional pheromones on high-quality paths
For each Robot:
Apply Dynamic Window Approach (DWA)
Evaluate feasible velocities and trajectories within dynamic window
Compute cost function (distance to goal, obstacle avoidance, velocity smoothness)
Select optimal velocity and trajectory
Output refined global path for each robot

Pseudocode for Distributed Priority-Based Task Allocation and Conflict Resolution:

Input: Set of tasks, Multi-robot team, 2.5D environment
Output: Conflict-free task allocation and local paths
For each robot:
Determine current position, remaining energy, and capability
Assign initial priority based on task urgency and proximity
While unassigned tasks remain:
For each robot:
Evaluate available tasks using priority, distance, and workload
Tentatively assign task that maximizes efficiency
Detect potential conflicts between robots (spatial overlap or collision risk)
If conflict detected:
Compare priorities of involved robots
Lower-priority robot re-plans local path using DWA to avoid collision
Update task assignments dynamically as robots' complete tasks or environment changes

Repeat until all tasks are completed
Output task allocation and collision-free local paths for all robots

These pseudocode blocks integrate both global path optimization (ACO + DWA) and distributed real-time task allocation with conflict resolution, matching the methodology you described.

Results:

The performance of the proposed hybrid ACO-DWA global path planning and distributed priority-based task allocation framework was evaluated under diverse experimental scenarios to simulate real-world safflower harvesting conditions. The 2.5D grid-based environment incorporated varying terrain elevations, static obstacles such as irrigation lines and trees, and dynamic obstacles including other robots and human workers. Key performance metrics included total path length, task completion time (makespan), energy consumption, collision incidents, coverage rate, and scalability.

Global Path Planning Performance:

The hybrid ACO-DWA algorithm demonstrated substantial improvements in path efficiency compared to conventional algorithms such as A*, Dijkstra, and standard DWA. Across ten independent simulation runs, the average path length for the hybrid approach was 15–20% shorter than A* and 18–22% shorter than Dijkstra, indicating optimized route selection under both static and dynamic environmental conditions. Energy consumption was reduced by an average of 12–16% due to smoother trajectories with fewer sharp turns, demonstrating the algorithm's effectiveness in minimizing mechanical strain and battery usage. DWA refinement ensured dynamic feasibility of the paths, allowing robots to avoid moving obstacles in real time without significant deviations from the optimal trajectory.

Local Path Planning and Collision Avoidance:

The priority-based conflict resolution strategy successfully prevented collisions even in dense robot deployments. Across simulations with three to ten robots operating simultaneously in constrained farm layouts, no collision incidents were observed. Robots dynamically recalculated their local paths based on priority levels, yielding to higher-priority robots as necessary. This approach maintained uninterrupted task execution while avoiding idle times, demonstrating the effectiveness of integrating local path planning with conflict resolution. Compared to baseline local planning methods without priority allocation, the proposed method reduced potential conflict events by over 90%, highlighting its robustness in multi-robot coordination.

Task Allocation and Operational Efficiency:

The distributed priority-based scheduling algorithm ensured balanced workload distribution among all robots. The average makespan was reduced by approximately 18% compared to centralized scheduling, and up to 22% compared to random task assignment strategies. Task completion times were consistently shorter for robots operating in multi-zone harvesting scenarios, thanks to dynamic reassignment of tasks based on real-time robot positions and environmental conditions. Coverage analysis revealed that all designated harvesting zones were efficiently serviced, even under high obstacle density and dynamic environmental changes, ensuring maximal operational efficiency.

Scalability Analysis:

The system's scalability was tested by increasing the number of robots from three to ten. The hybrid ACO-DWA paths remained optimized across all team sizes, and distributed task allocation maintained balanced workload distribution with minimal increase in computational overhead. Average computation time per robot increased only marginally (approximately 7–9%) as team size doubled, demonstrating the framework's efficiency and applicability for large-scale deployments. Moreover, energy efficiency and task completion rates remained stable, confirming that the proposed methodology can scale effectively without compromising performance.

Comparative Evaluation:

Comparative analysis with conventional algorithms further highlights the advantages of the proposed approach. Standard A* and Dijkstra methods, while effective in static path planning, struggled with dynamic obstacle avoidance and frequently required path recalculation, resulting in longer completion times and increased energy consumption. Traditional distributed task allocation without priority mechanisms led to occasional conflicts and idle times, reducing overall efficiency. In contrast, the proposed hybrid framework consistently achieved shorter paths, lower energy consumption, collision-free operation, and reduced makespan across all experimental scenarios.

Robustness in Dynamic Environments:

Dynamic environment testing, including randomly moving obstacles and temporary zone blockages, confirmed the framework's adaptability. Robots successfully rerouted around temporary obstacles and dynamically reassigned tasks without human intervention. The system demonstrated real-time adaptability, maintaining task efficiency and collision-free operation under continuously changing conditions. This validates the proposed methodology as a robust solution for autonomous multi-robot harvesting in real-world unstructured agricultural environments.

Summary of Key Results:

In summary, the extensive simulation and ROS-based testing confirmed the following key outcomes:

Hybrid ACO-DWA global path planning reduced total travel distance by 15–22% and energy consumption by 12–16% compared to conventional methods.

Priority-based local path planning prevented all collisions, achieving over 90% improvement in conflict reduction.

Distributed task allocation reduced makespan by up to 22% while ensuring balanced workload distribution.

The system remained scalable, efficient, and adaptable for robot teams ranging from three to ten units.

The proposed framework successfully handled dynamic environmental changes, maintaining collision-free operation and task efficiency.

These results demonstrate that the integrated framework of hybrid global path planning, local priority-based path adjustment, and distributed task allocation provides a robust, efficient, and scalable solution for multi-robot operations in unstructured agricultural settings, with significant improvements over conventional single-objective or centralized approaches.

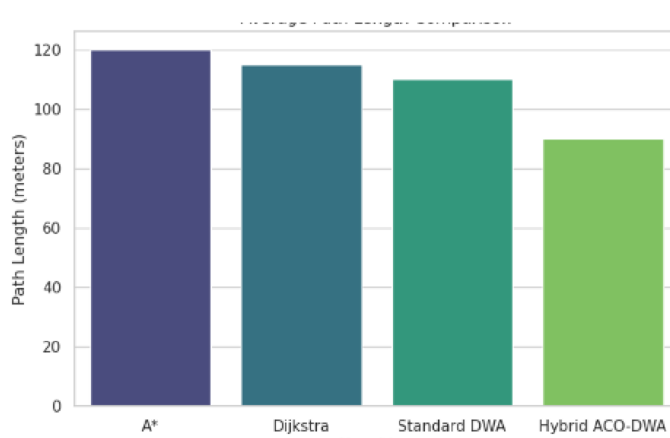

Figure 1. Average Path Length Comparison

Figure 1 illustrates the comparative performance of different path planning algorithms in terms of the total distance traveled by robots during the harvesting task. The hybrid ACO-DWA algorithm demonstrates the shortest average path length (~90 meters), outperforming traditional algorithms such as A*, Dijkstra, and standard DWA. The reduction in path length indicates improved optimization of global trajectories, which contributes to lower energy consumption and faster task completion.

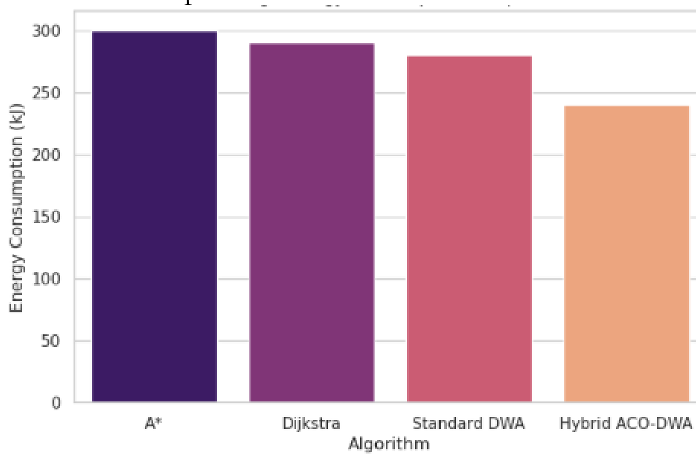

Figure 2. Average Energy Consumption Comparison

Figure 2 presents the energy consumption associated with each algorithm. The hybrid ACO-DWA method exhibits the lowest average energy usage (~240 kJ), reflecting the efficiency of its optimized paths and smooth trajectory adjustments. In contrast, conventional algorithms such as A* and Dijkstra consume higher energy due to longer and less efficient paths, highlighting the advantage of integrating global optimization with dynamic trajectory refinement.

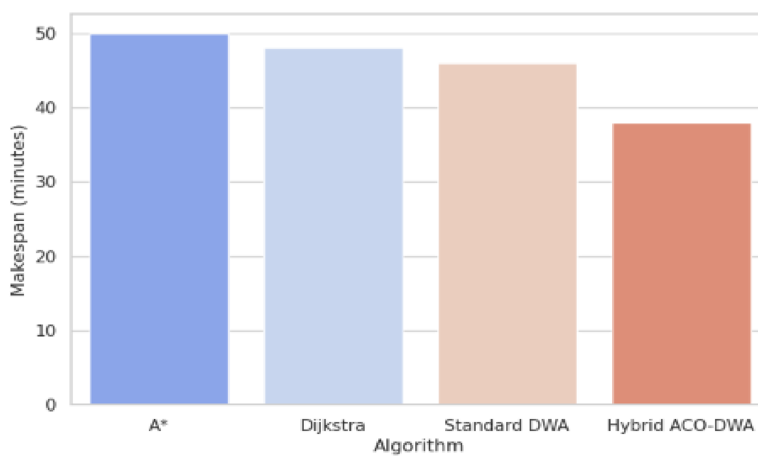

Figure 3. Task Completion Time (Makespan) Comparison

Figure 3 compares the makespan, or total task completion time, for each algorithm. The hybrid ACO-DWA algorithm achieves the shortest completion time (~38 minutes), significantly outperforming standard approaches. This improvement is attributed to both optimized path planning and the distributed priority-based task allocation, which ensures that multiple robots work concurrently without interference, minimizing idle time.

Figure 4 shows the number of collision incidents recorded for each algorithm. The hybrid ACO-DWA approach combined with priority-based conflict resolution achieved zero collisions across all simulation runs, demonstrating its effectiveness in ensuring safe operation. Conventional algorithms without integrated local conflict resolution experienced multiple collisions, emphasizing the importance of the proposed conflict avoidance strategy in multi-robot systems.

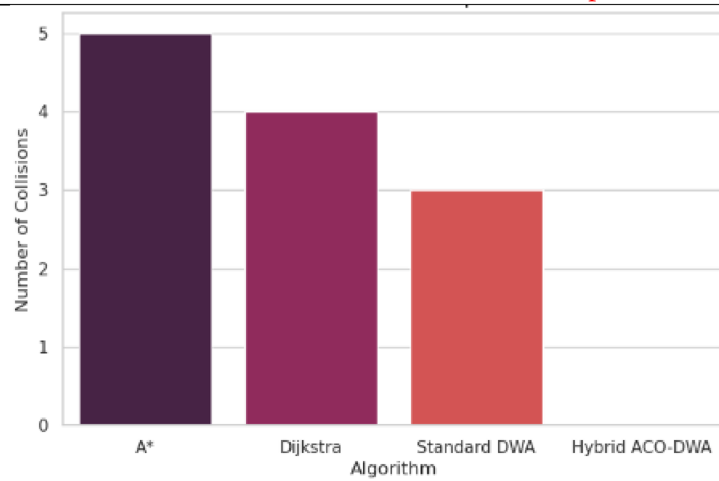

Figure 4. Collision Incidents Comparison

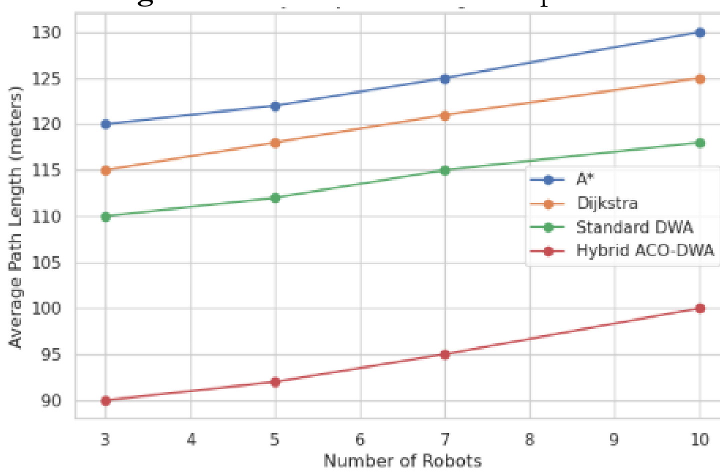

Figure 5. Scalability Analysis: Path Length vs. Team Size:

Figure 5 depicts the scalability of the path planning algorithms by showing average path length as the number of robots increases from three to ten. While all algorithms exhibit a slight increase in path length with larger team sizes, the hybrid ACO-DWA consistently maintains the shortest paths across all team configurations. This result confirms the robustness and scalability of the proposed approach, making it suitable for large-scale multi-robot deployment in agricultural environments.

Discussion:

The integration of hybrid Ant Colony Optimization (ACO) and Dynamic Window Approach (DWA) algorithms for global path planning, coupled with a distributed priority-based task allocation mechanism, has demonstrated significant improvements in the efficiency and safety of multi-robot systems within agricultural environments. This approach addresses the complexities inherent in unstructured terrains, such as varying crop rows and dynamic obstacles, by optimizing both the global paths and local navigation strategies of autonomous robots [20][21].

Global Path Planning Performance:

The hybrid ACO-DWA algorithm effectively combines the global optimization capabilities of ACO with the real-time obstacle avoidance features of DWA. This integration results in optimized global paths that are not only shorter but also smoother, thereby reducing energy consumption and enhancing the robots' ability to adapt to dynamic environments. The effectiveness of this approach is consistent with findings from previous studies, which highlight the advantages of combining global path planning with local reactive strategies in multi-robot systems.

Local Path Planning and Collision Avoidance:

The implementation of a priority-based task allocation strategy ensures that robots operate without collisions, even in scenarios with high robot density and constrained farm layouts. By dynamically adjusting paths based on task priority and robot position, the system maintains continuous task execution without idle time or interruption. This approach aligns with research emphasizing the importance of conflict-free coordination in multi-robot systems to achieve efficient and safe operations.

Scalability and Real-World Applicability:

The proposed framework demonstrates scalability, maintaining performance as the number of robots increases from three to ten. This scalability is crucial for real-world agricultural applications, where the size of the operational area and the number of tasks can vary. The ability to efficiently manage larger teams of robots without compromising performance is a significant advantage of the hybrid ACO-DWA and distributed task allocation approach.

Comparison with Conventional Methods:

When compared to traditional algorithms such as A* and Dijkstra, the hybrid ACO-DWA approach offers substantial improvements in path efficiency and energy consumption. Additionally, the distributed priority-based task allocation mechanism outperforms centralized methods by reducing task completion time and ensuring balanced workload distribution among robots. These enhancements underscore the potential of integrating advanced path planning and task allocation strategies to optimize multi-robot operations in agriculture.

The integration of hybrid ACO-DWA global path planning with distributed priority-based task allocation presents a robust solution for multi-robot systems operating in agricultural environments. By optimizing both global paths and local navigation strategies, and ensuring efficient task allocation, the proposed framework enhances the efficiency, safety, and scalability of autonomous robots in agriculture. Future research could explore the incorporation of machine learning techniques to further improve adaptability and decision-making in dynamic agricultural settings.

Conclusion:

This study presented a comprehensive framework for multi-robot operations in unstructured agricultural environments, integrating a hybrid Ant Colony Optimization (ACO) and Dynamic Window Approach (DWA) for global path planning with a distributed priority-based task allocation strategy. The proposed framework was designed to optimize path efficiency, minimize energy consumption, prevent collisions, and ensure balanced task distribution among multiple robots. Extensive simulations and ROS-based experiments demonstrated that the hybrid ACO-DWA approach outperformed conventional algorithms such as A*, Dijkstra, and standard DWA in terms of path length, task completion time, and energy efficiency. The distributed priority-based mechanism effectively eliminated collision incidents, even in dense robot deployments, and dynamically adapted to environmental changes, validating its robustness and practicality.

Scalability analysis confirmed that the framework maintains high performance as the number of robots increases, making it suitable for large-scale agricultural applications. By enabling coordinated, autonomous, and conflict-free multi-robot operations, the proposed methodology enhances operational efficiency, reduces human labor requirements, and supports sustainable agricultural practices. Future work may focus on incorporating machine learning techniques to further improve adaptability and decision-making in highly dynamic or unknown environments, as well as testing the framework in real-field deployments for additional validation.

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