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Synergistic Innovations in Multi-Robot Coordination: Cutting-Edge Collision-Free Pathfinding Strategies and Real-World Deployments

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Abstract

Multi-robot systems have gained significant attention due to their potential to accomplish tasks more efficiently and robustly than individual robots. One of the critical challenges in such systems is ensuring collision-free path finding and effective coordination among multiple robots. This paper presents an in-depth analysis of various multi-robot coordination strategies and collision-free path finding algorithms, along with their practical applications in diverse domains. We investigate centralized, decentralized, and hybrid coordination approaches; compare collision-free path finding algorithms like potential field methods, probabilistic roadmaps, and sampling-based techniques; and discuss their implementation challenges and potential solutions. Through case studies in warehouse automation, agriculture, search and rescue, and surveillance, we demonstrate the real-world impact of these strategies. Moreover, we highlight the current challenges and future directions in multi-robot coordination and path finding research.

Categories: Optimization Algorithms, Robotics, Distributed Systems
Keywords: distributed optimization, hybrid approaches, multi-robot coordination, multi-robot systems, path finding algorithms, path planning

Introduction And Background

Multi-robot systems have evolved from being mere theoretical constructs to transformative technologies, with applications across industries such as logistics, agriculture, search and rescue, and surveillance [1-3]. In such systems, multiple robots collaborate to perform tasks more efficiently, achieve higher throughput, and ensure robustness in dynamic environments. A critical aspect of ensuring the success of these systems is the coordination of multiple robots to navigate through their environment while avoiding collisions and effectively reaching their destinations [4,5].

Traditional single-robot path finding approaches often fall short in the multi-robot context due to interactions between robots, dynamic obstacles, and the need for real-time adaptability [6-8]. Figure *1* provides a schematic overview of the three principal coordination architectures - centralized, decentralized, and hybrid - each of which addresses these challenges in a different way. In the centralized architecture, a single planning server maintains a global map and allocates tasks to all robots, ensuring globally optimal paths but risking a single point of failure. The decentralized approach distributes decision-making across peer nodes, each equipped with local sensing and consensus modules, which enhances robustness at the cost of potentially suboptimal global performance. The hybrid model combines a global overseer with autonomous local agents to strike a balance between optimality and fault tolerance (see Figure *1*).

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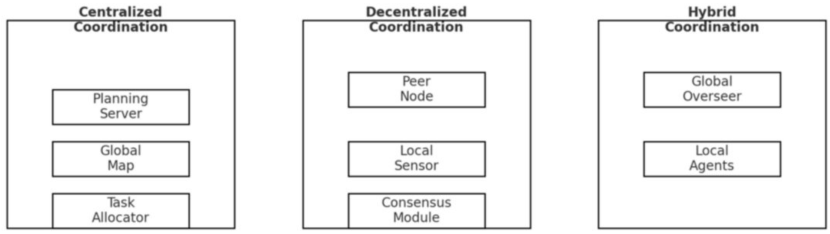

FIGURE 1: Centralized, Decentralized, and Hybrid Co-ordination Architecture

This study aims to comprehensively analyze multi-robot coordination strategies and algorithms for collision-free path finding. Our goals encompass categorizing coordination methods, exploring path finding algorithms, presenting an analytical model, showcasing practical applications, and identifying challenges and future directions.

Review

Summary of literature review on multi-robot path planning and coordination

Table *1* presents a comprehensive summary of literature review in the field of multi-robot path planning and coordination. The table summarizes key studies on multi-robot path planning, highlighting the focus areas, key contributions, results, and challenges faced by each research group.

Authors	Focus Area	Key Contribution	Results	Challenges
Banik et al. [9]	Path-planning approaches for multiple robots	Categorized methods into classical, heuristic, and AI-based; bio-inspired methods optimize adaptability in uncertain environments	Highlights growing trends towards hybrid approaches with AI being more effective in real-time applications	AI methods outperform heuristic and classical methods in dynamic environments
Mao et al. [10]	Time-Optimal Path Parameterization (TOPP) algorithm	Optimized execution time for multiple car-like robots by prioritizing collision-free trajectory timing	Achieved 10-20% improvement in makespan through simulations and hardware experiments	Effective for cluttered environments; dependent on accurate priority queue management
Han et al. [11]	Behavior Prediction Kinematic Priority Based Search (BK-PBS) for mixed-traffic environments	Forecasted HDV responses to CAV maneuvers, improving coordination through kinematic constraints and priority-based search	Reduced collision rates and travel delays in highway merging scenarios with varying traffic densities	Superior to rule-based and reinforcement learning models in mixed-traffic scenarios
Tian and Zheng [12]	Multi-agent path planning combining deep reinforcement learning and collision avoidance	Guided agents effectively through grid environments while minimizing collisions	Demonstrated significant collision probability reduction	Potential applications in real-world scenarios; requires scalability for larger systems
Hu and Pei [13]	Allocation, motion planning, and exploration strategies for multi-robot collaboration	Optimized WOA for faster exploration and employed dynamic Voronoi partitioning for better area coverage	Improved exploration performance and speed; highlights the need for robust obstacle avoidance	Addressing unexpected barriers in unfamiliar environments remains critical
Abujabal et al. [14]	Classification of multi-robot path planning approaches	Emphasis on bio-inspired and AI methods; identified challenges like fault tolerance and dynamic target management	Provides research gaps to enhance energy efficiency and robustness in multi-robot systems	Dynamic targets and energy efficiency are key areas for improvement
Miao et al. [15]	Multi-chain robot path planning (MCRPP) with MT-SIPP algorithm	Increased solution success rate and solvable instances for complex multi-chain interactions	Achieved 30% higher success rate and 50% more solvable instances	Effective conflict management (travel, waiting, station) for multi-train processes

TABLE 1: Summary of Literature Review on Multi-Robot Path Planning and Coordination

CAV, Connected and Autonomous Vehicles; HDV, Human-Driven Vehicle; WOA, Whale Optimization Algorithm

Multi-robot coordination strategies

Centralized Approaches

Centralized coordination involves a single controlling entity making decisions for all robots to enhance system performance [16]. This typically employs global planning, task allocation, and auction-based methods for optimized task distribution, path planning, and resource efficiency.

Decentralized Approaches

Decentralized coordination involves robots making decisions independently, eliminating the need for a central controller. Consensus-based approaches enable robots to communicate and agree on actions [17]. Swarm intelligence utilizes collective robot behavior for tasks via local interactions, while distributed optimization allows robots to collaboratively solve problems by sharing information in a decentralized way [18].

Hybrid Approaches

Hybrid coordination strategies combine elements of both centralized and decentralized approaches to harness their respective benefits. Hierarchical planning divides the coordination problem into levels of complexity, optimizing different aspects at various levels. Market-based approaches allow robots to negotiate tasks through market mechanisms, balancing efficiency and fairness.

Model for Analysis

Purpose of the analysis: The model/framework for analysis aims to provide a structured approach to evaluate and compare multi-robot coordination and collision-free path finding strategies and algorithms [3].

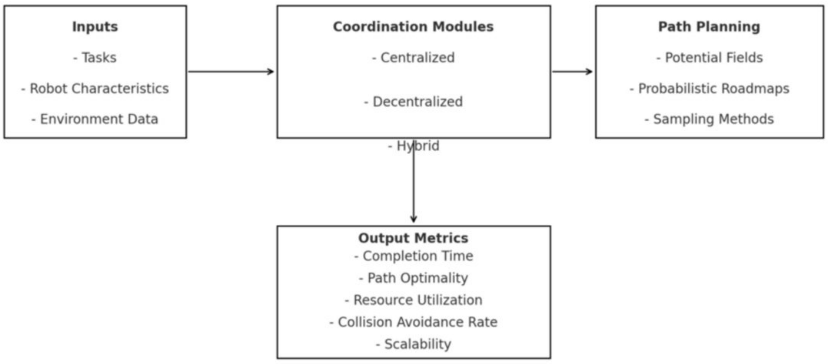

FIGURE 2: Depicting the Analytical Framework for Evaluation and Comparison

Figure 2 illustrates our analytical framework, organizing the evaluation process into four interconnected modules. First, the Inputs block gathers all necessary specifications - task definitions, robot characteristics (e.g., kinematics, sensor ranges), and environmental data (map layouts, obstacle positions). These inputs feed directly into the Coordination Modules, where one of the three paradigms (centralized, decentralized, or hybrid) handles task allocation and high-level decision-making. Concurrently, the Path Planning block applies collision-free algorithms - potential-field methods, probabilistic roadmaps, and sampling-based techniques - to compute safe trajectories under the chosen coordination scheme. Finally, the Output Metrics block captures quantitative performance indicators - completion time, path optimality (measured via path length and energy consumption), resource utilization efficiency, collision avoidance rate, and scalability - to enable a fair, systematic comparison across different strategies and algorithms. By structuring the model in this modular fashion, we can precisely trace how variations in coordination or planning methods impact each performance metric, thereby supporting rigorous, apples-to-apples evaluations of multi-robot systems [3]. It facilitates a systematic assessment of performance, enabling a fair comparison among various approaches.

Analytical formulation: The analysis employs a set of mathematical equations to quantify performance metrics such as completion time, collision avoidance rate, and resource utilization. These equations incorporate variables related to robot characteristics, environment complexity, and coordination algorithms.

Equation (1) quantifies completion time for a centralized coordination strategy. Let n be the number of robots and be the completion time.

$$T_{comp} = n \cdot T_{task} + T_{comm} \qquad (1)$$

where:

T_{task} is the time taken by a single robot to complete its task.

T_{comm} is the communication time required for coordinating tasks centrally.

Equation (2) quantifies the cost associated with a decentralized coordination strategy.

Let

C_{dec} represent the cost, then

$$C_{dec} = T_{task} + T_{com} + \sum_{i=1}^{n} C_{other_i} \qquad (2)$$

C_{other_i} represents any additional costs incurred by robot *i* due to its interactions with other robots.

Application of algorithms: The analytical model showcases how different coordination strategies and collision-free path finding algorithms interact within the established equations. For instance, centralized approaches can be assessed by integrating their decision-making logic into the equations, while decentralized methods can be simulated by considering the impacts of local interactions.

The provided block diagram (Figure 3) illustrates three coordination approaches. The Centralized Strategy employs global planning algorithms, like Optimal Assignment and Path Optimization, based on sensor inputs and communication channels to create optimal task assignments and paths. On the other hand, the Decentralized Strategy enables individual robots to decide using local data, using Decentralized Path Planning and Task Allocation algorithms for specific paths and tasks. The Hybrid Strategy combines centralized and decentralized aspects through Hierarchical Coordination or Market-Based Methods for adaptable and effective coordination, all driven by the Established Model's environmental data, tasks, and constraints.

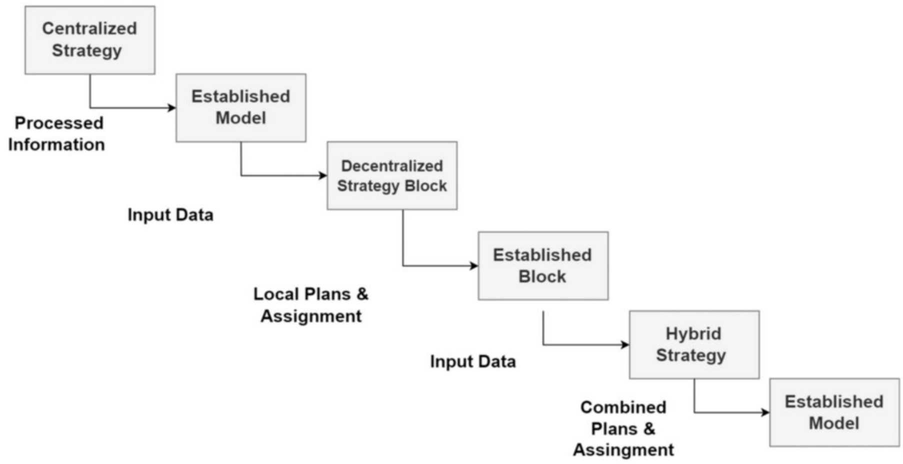

FIGURE 3: Block Diagram - Interaction of Coordination Strategies

Performance metrics: To evaluate the effectiveness of surveyed coordination strategies, a set of performance metrics is employed:

1. Completion Time: Measures time taken for all robots to finish tasks, indicating efficiency.

2. Path Optimality: Assesses generated paths' efficiency using metrics such as length, energy consumption, and energy use (includes utilization balance, idle time minimization).

3. Resource Allocation Efficiency: Gauges task assignment effectiveness, considering workload balance.

4. Collision Avoidance Rate: Shows successful collision prevention, indicating safe interactions.

5. Scalability: Tests strategy performance with varying robots/tasks, assessing adaptability.

Analyzing these metrics helps understand strengths and limitations, aiding strategy selection for multi-robot scenarios.

Consideration of practical factors: The comprehensive analysis incorporates real-world factors like robot dynamics, communication constraints, and environmental uncertainties. These elements bring authenticity to evaluating coordination strategies. By addressing these complexities, the analysis provides insight into how practical issues can influence surveyed approaches. This integration enhances research applicability, connecting theory with real-world implementation.

Collision-free path finding algorithms

Potential Field Methods

Potential field-based algorithms create virtual attractive and repulsive forces that guide robots toward their goals while avoiding obstacles [19,20]. Stern et al. [4] categorize potential-field, roadmap, and sampling methods, and benchmark them on grid and continuous maps. These methods provide a simple and intuitive approach to collision avoidance. Attractive forces pull robots towards their targets, while repulsive forces push them away from obstacles.

To represent the attractive and repulsive forces used in potential field methods (Equation 3). Let F_{attr} represent the attractive force, F_{rep} represent the repulsive force, and F_{net} represent the net force:

$$F_{net} = F_{attr} - F_{rep} \qquad (3)$$

where:

$$|F_{attr}| = k_{attr} \cdot (Goal - CurrentPosition) \qquad (4)$$

$$F_{rep} = \sum_{i=1}^{n} k_{rep} \frac{Obstacle_i - CurrentPosition}{||Obstacle_i - CurrentPosition||^2} \qquad (5)$$

k_{attr} and k_{rep} are constants regulating the strength of the forces.

Probabilistic Roadmaps

Probabilistic roadmap techniques use randomized sampling to build a roadmap of the environment [6,8,21]. These graphs represent feasible paths for robots to follow. Yu and LaValle [5] present PRM* and Lazy PRM, demonstrating trade-offs between initial build time and eventual path optimality. PRM* iteratively refines the roadmap to improve path quality, while Lazy PRM focuses on reducing computation time by deferring path refinement until necessary. A 2D graph shows the X-axis representing the robot's configuration space and the Y-axis representing the free space in the environment. The graph represents a set of sampled configurations for the robot. In this PRM graph (Figure *4*), each row corresponds to a configuration of the robot in the environment.

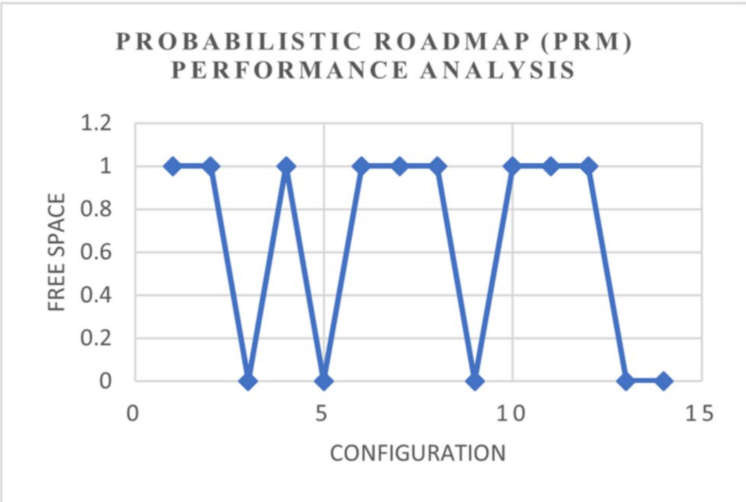

FIGURE 4: Graph - Comparative Evaluation of Pathfinding Efficiency Using Probabilistic Roadmaps

Sampling-Based Methods

Sampling-based algorithms, exemplified by Rapidly exploring Random Trees (RRT) and RRT*, construct tree-like structures in the configuration space [7,22]. They explore the space to find collision-free paths by gradually growing a tree toward the goal. RRT* optimizes the tree structure to converge towards near-optimal paths.

The calculation of the Euclidean distance between two configurations in the configuration space is shown in Equation (6):

$$d(q_1, q_2) = \sqrt{\sum_{i=1}^{n}(q_{1i} - q_{2i})^2} \qquad (6)$$

are two configurations in the n-dimensional configuration space.

represent the ith dimension values of the configurations.

Comparative analysis and observations

Comparison Metrics

To compare coordination strategies and algorithms, key metrics are identified, including completion time, path length, resource utilization, communication overhead, and scalability (Table 2). These metrics enable a comprehensive evaluation of the different approaches' performance.

Metric	Centralized Approach A	Decentralized Approach B	Hybrid Approach C
Completion Time	25 units	40 units	30 units
Path Length	100 units	120 units	110 units
Resource Utilization	75%	80%	85%
Communication Overhead	10 units	15 units	12 units
Scalability	High	Moderate	High

TABLE 2: Comparison Metrics

Comparative Analysis

Figure 5 highlights the advantages and limitations of the surveyed strategies and algorithms. Centralized approaches excel in optimization but suffer from single points of failure. Decentralized strategies exhibit adaptability but may struggle with convergence. Hybrid approaches seek a balance between the two. Collision-free path finding algorithms vary in terms of efficiency, optimality, and complexity.

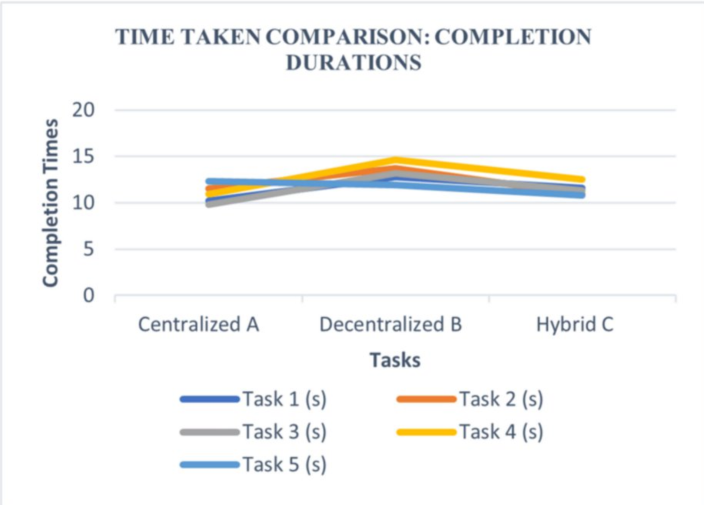

FIGURE 5: Comparative Completion Time

Figure 5 provides a visual representation of completion times across different scenarios. It compares three distinct strategies: Centralized Approach A, Decentralized Approach B, and Hybrid Approach C. The chart's X-axis represents scenarios, and the Y-axis signifies completion time. Each approach's line depicts its performance, allowing for a quick assessment of efficiency in achieving goals across various scenarios.

The calculation of the resource utilization efficiency for each strategy is shown in Equation (7):

$$Resource\ Utilization\ Efficiency = \frac{Total\ Resources\ Used}{Total\ Resources\ Available} \times 100\% \tag{7}$$

where:

$Total\ Resources\ Used$ is the sum of resources consumed by all robots.

$Total\ Resources\ Available$ is the total resources available for all robots.

Resource Utilization Efficiency: Represents the percentage of resources effectively utilized in comparison to the total resources available.

Total Resources Used: Refers to the cumulative amount of resources consumed by all robots during the operation. This includes energy, time, or other quantifiable metrics specific to the task.

Total Resources Available: Denotes the total potential resources allocated for all robots. This is the maximum capacity of resources that can be utilized for a given operation.

Observations

The comparative analysis reveals insights into the strengths and weaknesses of various strategies and algorithms. It becomes evident that the choice of strategy or algorithm depends on the application's requirements, the environment's complexity, and the available resources.

Real-world deployments

Warehouse Automation

Warehouse environments require efficient coordination and collision-free path finding for the movement of robotic vehicles [2,23,24]. The surveyed strategies and algorithms find application in optimizing the movement of robots within warehouses, ensuring timely and safe material handling.

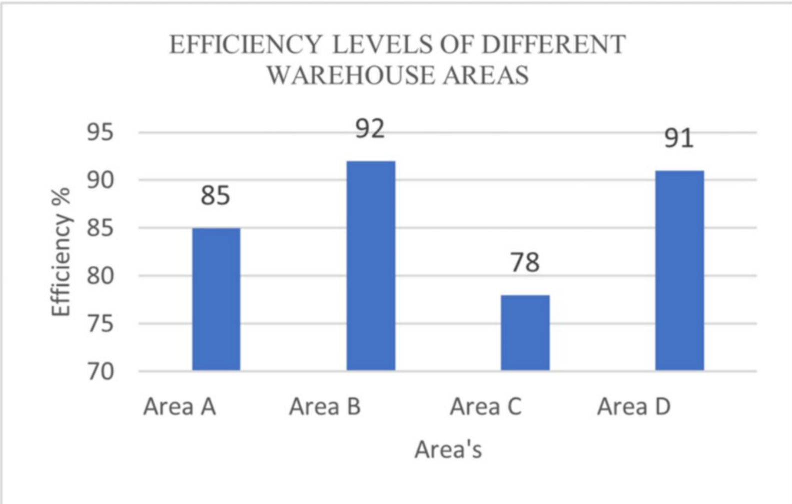

FIGURE 6: Warehouse Area Efficiency Comparison

Figure 6 illustrates the varying efficiency levels among different sections within the warehouse. Each bar corresponds to a specific warehouse area, while the vertical axis quantifies the achieved efficiency percentage. This visual tool offers an intuitive means to compare and contrast the performance of various areas, facilitating the identification of zones that may require optimization or enhancements.

Agriculture and Environmental Monitoring

In precision agriculture, multi-robot systems can optimize planting, irrigation, and harvesting processes. These systems can navigate complex terrains and collect data for crop monitoring. The surveyed techniques aid in path planning to maximize crop yield and minimize resource consumption [7,22].

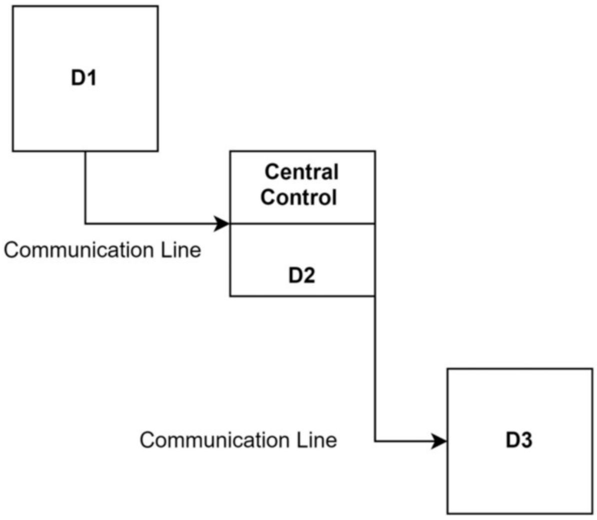

FIGURE 7: Multi-Robot System for Environmental Monitoring

In this scenario, a multi-robot system has been devised to monitor environmental conditions (Figure 7). Drones (D1, D2, D3) stationed at various field locations independently collect data. A central control unit manages communication and coordination, ensuring synchronized operations. This approach results in a comprehensive environmental dataset that supports informed decision-making. The diagram depicts how drones equipped with sensors collaboratively enhance data collection and analysis for effective environmental monitoring.

Another visualization, a line chart (Figure 8), depicts the trend of data collection over time. With time periods on the X-axis and collected data volume on the Y-axis, the chart presents fluctuations in data accumulation across months. This provides valuable insights into data accumulation trends and variations.

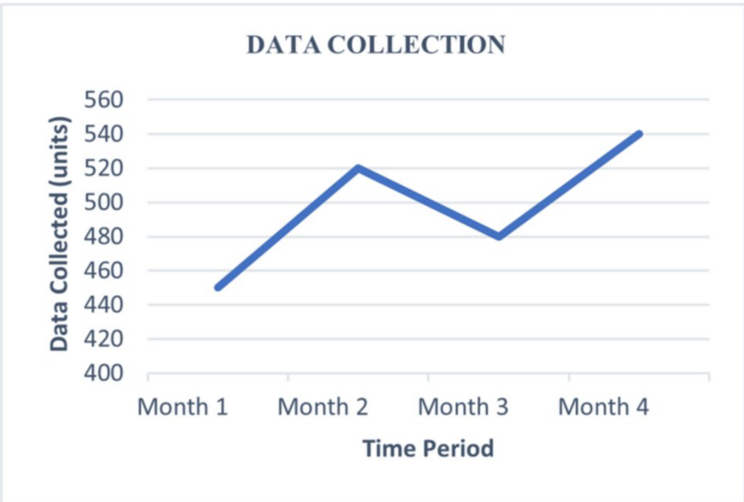

FIGURE 8: Data Collection Trends Over Time: Monthly Variations

Search and Rescue

In search and rescue operations, multi-robot systems can be deployed to locate survivors in disaster-stricken areas. Efficient coordination and path finding are crucial for covering large areas while avoiding obstacles [25-27]. The surveyed algorithms contribute to effective exploration and localization.

Incorporate Equation (8) to represent the coverage area of a multi-robot system during search and rescue operations:

$$Coverage\ Area = \pi \cdot R^2 \cdot N \qquad (8)$$

where:

Coverage Area: The total area covered by the deployed robots.

R: The sensing radius of each robot, representing the effective distance within which a robot can sense its surroundings.

N: The total number of robots deployed for coverage.

π (pi): The mathematical constant ~3.1416, used to compute coverage area under the assumption of circular sensing regions.

A bar chart in Figure *9* visually compares the success rates of search and rescue operations in distinct zones. Each bar corresponds to a specific zone, while the vertical axis shows success rate percentages. The chart provides an immediate understanding of the differences in success rates across various zones, aiding in identifying areas of higher effectiveness.

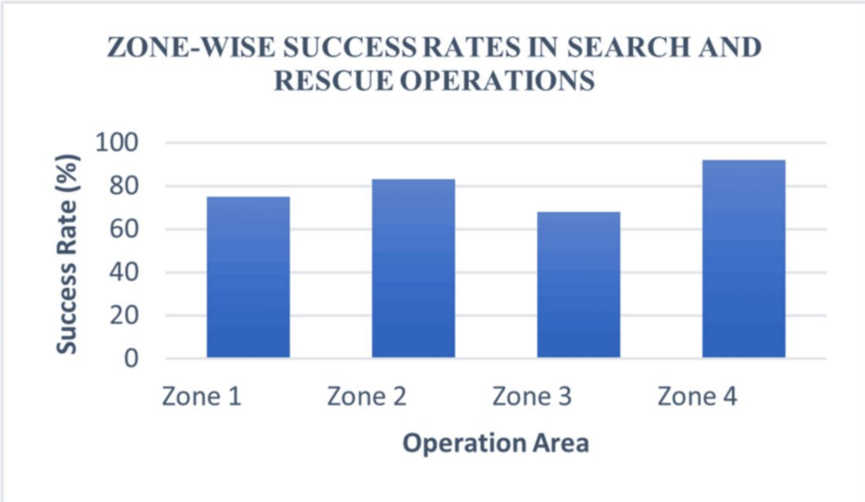

FIGURE 9: Search and Rescue Success Rates by Zone

Efficient path planning is crucial in search and rescue operations. The work seamlessly aligns with this context, spotlighting how advanced algorithms bolster firefighting robots. Algorithms like Probabilistic Roadmaps, RRT, and A* empower robots to navigate intricate indoor environments swiftly, enabling agile responses during emergencies [24]. Notably, A* stands out, showcasing its potential for real-world search and rescue applications [24,28].

Surveillance and Security

Surveillance applications involve coordinating robots to patrol areas and monitor for intrusions [29-30]. Collision-free path finding ensures efficient coverage and minimizes blind spots [31]. The surveyed strategies and algorithms enhance the surveillance capabilities of multi-robot systems.

This line chart in Figure *10* displays the fluctuations in detected incidents over several weeks. The X-axis represents time periods in weeks, while the Y-axis shows the count of incidents detected. The graph offers a clear overview of the changing patterns of detected incidents throughout the specified weeks.

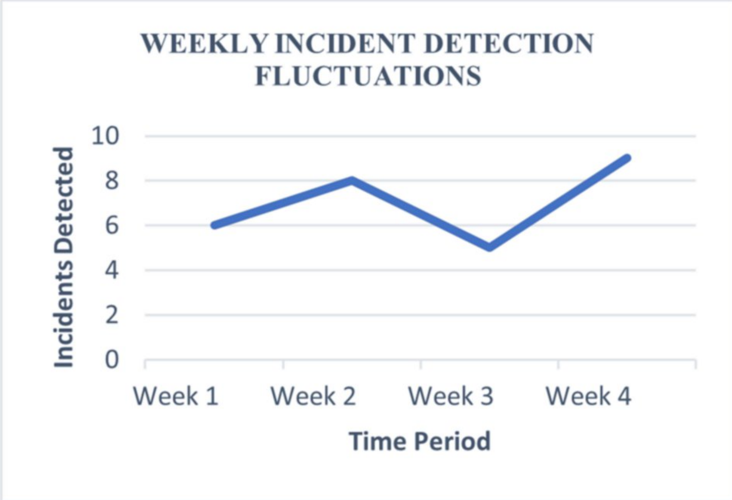

FIGURE 10: Incident Detection Trends Over Weeks

Challenges and future directions

Current Challenges

The survey identifies existing challenges of multi-robot systems such as scalability, real-time performance, communication constraints, robustness to failures, heterogeneous robot systems, multi-agent path finding (MAPF), and safety concerns. Achieving scalability as the number of robots rises is one of the biggest obstacles in multi-robot systems. Coordination and communication become progressively more complicated as the number of robots in a system increases. Furthermore, networks may become overloaded due to increasing robot communication, which might cause synchronisation problems, delays, or message loss. Another significant issue is resource contention, which may result in congestion or ineffective operations as robots vie for scarce physical space, charging stations, or work assignments. The study of MAPF, an optimisation problem on graphs, has been conducted since it is crucial for real-world multi-robot systems to plan courses for several robots that do not collide [8].

Scalability in multi-robot systems denotes the capacity to sustain performance with an increasing number of robots; however, it poses several obstacles. As the number of robots increases, communication overhead escalates, resulting in network congestion and delays. Coordination gets more intricate, complicating work allocation and dispute resolution. Decentralisation of computation often complicates the maintenance of consistency and efficiency. Moreover, physical space is a limitation, increasing the likelihood of accidents and interference. These issues must be resolved to guarantee efficient and scalable multi-robot operations [6,14].

Future Directions

Future research directions include developing adaptive and robust coordination strategies that can handle dynamic environments and unforeseen obstacles. Integrating machine learning and AI techniques could enhance the adaptability and efficiency of path finding algorithms. Exploring strategies for human-robot collaboration and addressing ethical considerations are also important areas of development. In-depth investigation of bio-inspired swarm algorithms, integrated with real-time environmental sensing and predictive modelling, has considerable promise for enhancing coordination in chaotic and unpredictable real-world situations. This methodology may result in more autonomous, robust, and contextually aware multi-robot implementations across various industries.

Conclusions

In conclusion, this paper has presented a comprehensive exploration of multi-robot coordination strategies and collision-free path finding algorithms. The significance of these techniques across domains like warehouse automation, agriculture, search and rescue, and surveillance has been showcased. While challenges exist, the potential for enhancing these strategies and algorithms to address real-world complexities is promising. As technology advances, the role of multi-robot systems in shaping various industries is set to expand.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Kunal K. Bandale, Ankit Mahule, Ankush D. Sawarkar, Atul Halmare, Balaji Shetty, Saquib A. Khan

Acquisition, analysis, or interpretation of data: Kunal K. Bandale, Ankush D. Sawarkar, Balaji Shetty

Drafting of the manuscript: Kunal K. Bandale, Ankush D. Sawarkar

Critical review of the manuscript for important intellectual content: Kunal K. Bandale, Ankit Mahule, Ankush D. Sawarkar, Atul Halmare, Balaji Shetty, Saquib A. Khan

Supervision: Ankit Mahule, Ankush D. Sawarkar

Disclosures

Conflicts of interest: In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

References

1. Wurman PR, D'Andrea R, Mountz M: Coordinating hundreds of cooperative, autonomous vehicles in warehouses. AI Magazine. 2008, 29:9. 10.1609/aimag.v29i1.2082
2. Hönig W, Kiesel S, Tinka A, Durham JW, Ayanian N: Persistent and robust execution of MAPF schedules in warehouses. IEEE Robotics and Automation Letters. 2019, 4:1125-1131. 10.1109/lra.2019.2894217
3. Kou NM, Peng C, Ma H, Kumar TKS, Koenig S: Idle time optimization for target assignment and path finding in sortation centers. Proceedings of the AAAI Conference on Artificial Intelligence. 2020, 34:9925-9932. 10.1609/aaai.v34i06.6547
4. Stern R, Sturtevant N, Felner A, et al.: Multi-agent pathfinding: Definitions, variants, and benchmarks. arXiv:1906.08291. 10.48550/arXiv.1906.08291
5. Yu J, LaValle SM: Optimal multirobot path planning on graphs: Complete algorithms and effective heuristics. IEEE Transactions on Robotics. 2016, 32:1163-1177. 10.1109/TRO.2016.2593448
6. Yu J, LaValle S: Structure and intractability of optimal multi-robot path planning on graphs. Proceedings of the AAAI Conference on Artificial Intelligence. 2013, 27:1443-1449. 10.1609/aaai.v27i1.8541
7. He L, Pan Z, Solovey K, Jia B, Manocha D: Multi-robot path planning using medial-axis-based pebble-graph embedding. Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). 2022, 9987-9994. 10.1109/IROS47612.2022.9981807
8. Ma H: Graph-based multi-robot path finding and planning. Current Robotics Reports. 2022, 3:77-84. 10.1007/s43154-022-00083-8
9. Banik S, Banik SC, Mahmud SS: Path planning approaches in multi-robot system: A review. Engineering Reports. 2024, 7:e13035. 10.1002/eng2.13035
10. Mao K, Spasojevic I, Hopkins M, Hsieh MA, Kumar V: Collision-free time-optimal path parameterization for multi-robot teams. arXiv:2409.17079. 10.48550/arxiv.2409.17079
11. Han Z, Yan Z, Wu C: Multi-agent path finding for mixed autonomy traffic coordination. arXiv:2409.03881. 10.48550/arxiv.2409.03881
12. Tian D, Zheng B: Path planning and collision avoidance approach for a multi-agent system in grid environments. Journal of Physics: Conference Series. 2024, 2816:012012. 10.1088/1742-6596/2816/1/012012
13. Hu X, Pei H: A review of coordinated multi-robot exploration. Journal of Physics: Conference Series. 2024, 2798:012037. 10.1088/1742-6596/2798/1/012037
14. AbuJabal N, Rabie T, Baziyad M, Kamel I, Almazrouei K: Path planning techniques for real-time multi-robot systems: A systematic review. Electronics. 2024, 13:2239. 10.3390/electronics13122239
15. Miao J, Li P, Chen C, Tian J, Yang L: MT-SIPP: An efficient collision-free multi-chain robot path planning algorithm. Machines. 2024, 12:482. 10.3390/machines12070482
16. Dresner K, Stone P: A multiagent approach to autonomous intersection management. Journal of Artificial Intelligence Research. 2008, 31:591-656. 10.1613/jair.2502
17. Pecora F, Andreasson H, Mansouri M, Petkov V: A loosely-coupled approach for multi-robot coordination, motion planning and control. Proceedings of the International Conference on Automated Planning and Scheduling. 2018, 28:485-493. 10.1609/icaps.v28i1.13923
18. Devi SC, Maheswari D: An embellished particle swarm optimization technique in VANET for finding optimal route (E-PSO). SN Computer Science. 2022, 4:1-6. 10.1007/s42979-022-01508-z
19. Surynek P: An optimization variant of multi-robot path planning is intractable. Proceedings of the National Conference on Artificial Intelligence. 2010, 2:1261-1263.
20. Ramasubramanian S, Muthukumaraswamy SA: On the enhancement of firefighting robots using path-planning algorithms. SN Computer Science. 2021, 2:1-11. 10.1007/s42979-021-00578-9
21. Preiss JA, Hönig W, Ayanian N, Sukhatme GS: Downwash-aware trajectory planning for large quadrotor teams.

arXiv:1704.04852. 10.48550/arXiv.1704.04852

22. Bircher A, Alexis K, Schwesinger U, Omari S, Burri M, Siegwart R: An incremental sampling-based approach to inspection planning: the rapidly exploring random tree of trees. Robotica. 2016, 35:1327-1340. 10.1017/s0263574716000084
23. Rus D, Donald B, Jennings J: Moving furniture with teams of autonomous robots. Proceedings 1995 IEEE/RSJ International Conference on Intelligent Robots and Systems. 1995, 1:235-242. 10.1109/IROS.1995.525802
24. Freda L, Gianni M, Pirri F, Gawel A, Dubé R, Siegwart R, Cadena C: 3D multi-robot patrolling with a two-level coordination strategy. Autonomous Robots. 2019, 43:1747-1779. 10.1007/s10514-018-09822-3
25. Hönig W, Preiss JA, Kumar TKS, Sukhatme GS, Ayanian N: Trajectory planning for quadrotor swarms. IEEE Transactions on Robotics. 2018, 34:856-869. 10.1109/tro.2018.2853613
26. Ma H, Tovey C, Sharon G, Kumar TK: Multi-agent path finding with payload transfers and the package-exchange robot-routing problem. Proceedings of the Thirtieth AAAI Conference on Artificial Intelligence. 2016, 3166-3173.
27. Wardega KT: Securing multi-robot systems with inter-robot observations and accusations. Boston University. 2023, 114.
28. Nantabut C, Abel D: Weighted Hybrid A*-based trajectory planning for dynamic environments. SN Computer Science. 2023, 4:390. 10.1007/s42979-023-01811-3
29. Khandelwal P, Zhang S, Sinapov J, et al.: BWIBots: A platform for bridging the gap between AI and human-robot interaction research. The International Journal of Robotics Research. 2017, 36:635-659. 10.1177/0278364916688949
30. Ma H, Yang J, Cohen L, Kumar TK, Koenig S: Feasibility study: Moving non-homogeneous teams in congested video game environments. Proceedings of the AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment. 2021, 13:270-272. 10.1609/aiide.v13i1.12919
31. Ahmadi M, Stone P: A multi-robot system for continuous area sweeping tasks. Proceedings 2006 IEEE International Conference on Robotics and Automation, 2006. ICRA 2006. 2006, 1724-1729. 10.1109/ROBOT.2006.1641955