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Research Article

Navigating the Future: An In-Depth Exploration of Quantum Computing in Swarm Intelligence based Multi Robot Systems

Vandana Dabass [1], Suman[2]

[1]*Research Scholar, Department of Computer Science & Engineering, Deenbandhu Choturam university of science & technology, Murthal, India vandanadabass@gmail.com*

[2]*Professor, Department of Computer Science & Engineering, Deenbandhu Choturam university of science & technology, Murthal, India suman.cs@dcrust.org*

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ABSTRACT

In recent times, Multi-Robot Systems (MRS) have garnered extensive attention for their versatility and potential to tackle diverse real-world challenges. Among the myriad problems these systems aim to resolve the Multi-Robot Task Allocation (MRTA) stands out due to its pivotal role in optimizing collective robot performance. MRTA focuses on the efficient distribution of tasks among a group of robots, with objectives often centered around minimizing operational time or maximizing efficiency. Delving into optimization-based approaches, we critically review various studies to highlight their strengths and limitations. This examination reveals the innovative strategies that have emerged in the field, underscoring both the achievements and the persisting challenges within MRTA research. By identifying these gaps, we aim to outline potential directions for future inquiry, suggesting pathways for advancements in MRS efficiency and application breadth using quantum computing. The integration of quantum computing into swarm-based multi-robot systems is an emerging interdisciplinary field that promises to enhance the capabilities of robotic collectives. By leveraging principles of quantum mechanics, such as superposition and entanglement, these systems can achieve more efficient coordination, decision-making, and problem-solving.

Furthermore, this paper presents evolution of MRTA strategies over recent years, identifying prevalent methods and noting shifts in research focus. Through this analysis, we aim to expose a extensive overview of the state-of-the-art in MRTA, encouraging further exploration and interdisciplinary collaboration. The integration of quantum computing into Multi-Robot Task Allocation (MRTA) represents a significant advancement in the field, promising to enhance the efficiency and capabilities.

Keywords: Quantum Computing, Swarm intelligence, MultiRobot Task Allocation (MRTA),Superposition , Problem solving.

INTRODUCTION

Robotic systems have become an indispensable part of modern industrial, medical, and exploratory applications, driving innovations that transcend traditional limitations. As such, they represent a confluence of interdisciplinary research efforts, embodying the integration of mechanical engineering, computer science, and cognitive sciences to enhance their autonomy, efficiency, and interaction capabilities with the physical world. These systems, characterized by their precision, repeatability, and adaptability, leverage advanced algorithms and sensor technologies to perform complex tasks in environments that are often inaccessible or hazardous to humans. Additionally, the complexity of tasks demands collaboration among robots, enhancing the utility of Multi-Robot Systems (MRS) over single robots. Multi-robot systems (MRS) represent an advanced paradigm in autonomous robotics, wherein multiple robots collaboratively engage in tasks that often exceed the capabilities of a solitary unit. The expansion of MRS has been propelled by advancements in artificial intelligence, robotics, and communication technologies, which have facilitated the design and deployment of complex robotic systems[1]. These systems are characterized not only by their collective operation but also by their ability to adapt to dynamically changing environments, making them suitable for a diverse range of applications—from industrial automation and rescue operations to healthcare and environmental monitoring. Central to understanding MRS is the evaluation of their architecture, which frames the interaction dynamics of individual robots and their shared environment. Various architectures exist, including centralized, decentralized, and hybrid models. Centralized architectures typically involve a dominant controller that coordinates activities among robots, whereas decentralized systems afford individual robots greater autonomy in decision-making [2]. Hybrid models seek to blend these approaches, leveraging the strengths of both by allowing for centralized oversight when beneficial while maintaining a level of autonomy for individual robots. The communication strategies employed in MRS are critical to their operational efficacy. These strategies can be classified into direct and indirect communication. Direct communication, often facilitated through wireless protocols, enables robots to share information in real time. This allows for rapid decision-making and dynamic task reallocation[3]. Conversely, indirect communication, such as stigmergy, involves robots leaving cues in the environment for others to interpret, facilitating coordination without direct interaction. Understanding the intricacies of these communication strategies is vital, as it directly impacts the performance and reliability of collaborative tasks. The integration of quantum computing into swarm intelligence-based multi-robot systems is an emerging interdisciplinary field that promises to enhance the capabilities of robotic collectives. By leveraging principles of quantum mechanics, such as superposition and entanglement, these systems can achieve more efficient coordination, decision-making, and problem-solving.

Applications of MRS are diverse, reflecting their adaptability across multiple domains. In military contexts, for example, MRS can execute reconnaissance missions, engage in target acquisition, and enhance battlefield situational awareness through cooperative strategies. In the healthcare sector, they have been utilized in surgical assistance, where multi-robot systems can collaborate to manage instruments and monitor patient vitals simultaneously [5]. Additionally, MRS find applications in disaster response scenarios, where they can perform search and rescue operations in hazardous environments, effectively covering larger areas than a single robot.

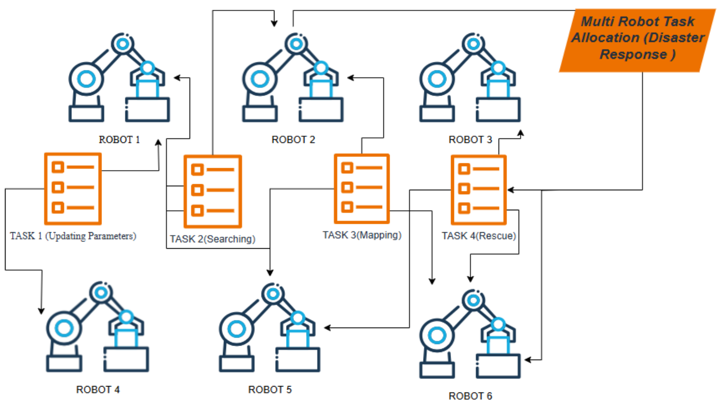


Fig 1: MRTA problem presentation

The difficulty of assigning appropriate tasks to specific robots within an MRS is central to Multi-Robot Task Allocation (MRTA) (Figure 1), and is the focal point of this study. MRTA is critical for coordinating numerous robots to complete various tasks under specific constraints, where intentional cooperation proves essential. This process can be perceived as a supervisory control layer within the robots' architecture, enabling concurrent task execution through collective behavior. Mobile robots, classified into land-based, air-based, and water-based types, perform a wide range of functions, from delivery to debris removal, demonstrating their operational versatility. Despite the advantages afforded by MRS, several challenges remain in the realm of coordination and collaboration among multiple robots. One significant concern is the issue of scalability; as the number of robots increases, the complexity of coordination also rises, often leading to potential bottlenecks or inefficient resource allocation [4] Likewise, ensuring reliable communication amidst potential failures in network connectivity is paramount. Robots must be equipped to adapt to changing communication conditions, necessitating robust algorithms that can handle disruptions while maintaining operational integrity. The classification of tasks plays a pivotal role in the formulation of Multi-Robot Task Allocation (MRTA) problems. Predominantly, tasks can be categorized into two principal types. The first type involves tasks that are singularly assigned to and completed by one robot, while the second type comprises tasks that are divisible into sub-tasks, each potentially assigned to different robots [29]. Within this framework, tasks are further delineated as follows:

- **Elemental or Atomic Tasks:** These are indivisible and must be executed in their entirety by a single robot.
- **Simple Tasks:** A simple task may either be elemental or capable of division into sub-tasks, all of which are allocated to single robot.
- **Compound Tasks:** These tasks are divisible into different tasks, with each sub-task assigned to different robots. A compound task is characterized by a single, defined decomposition.
- **Complex Tasks:** Representing the most intricate category, complex tasks feature multiple potential decompositions, with at least one decomposition being distributable among several robots. The sub-tasks within a complex task themselves be complex, simple or compound.

To further refine the classification of MRTA [30] proposed a taxonomy that incorporates considerations of robot capabilities, task requirements, and temporal dynamics:

- **Single-task Robots (ST) / Multi-task Robots (MT):** Differentiates between robots that are limited to executing a single task at any given time and those capable of undertaking multiple tasks concurrently.
- **Single-robot Tasks (SR) / Multi-robot Tasks (MR):** Distinguishes tasks based on whether they can be accomplished by a single robot or necessitate collaboration among multiple robots.
- **Instant-Assignment (IA) / Time-Extended Assignment (TA):** Contrasts scenarios where robots are assigned tasks for immediate execution without future planning, against contexts that allow for the assignment of a sequence of tasks to robots over a planned horizon.

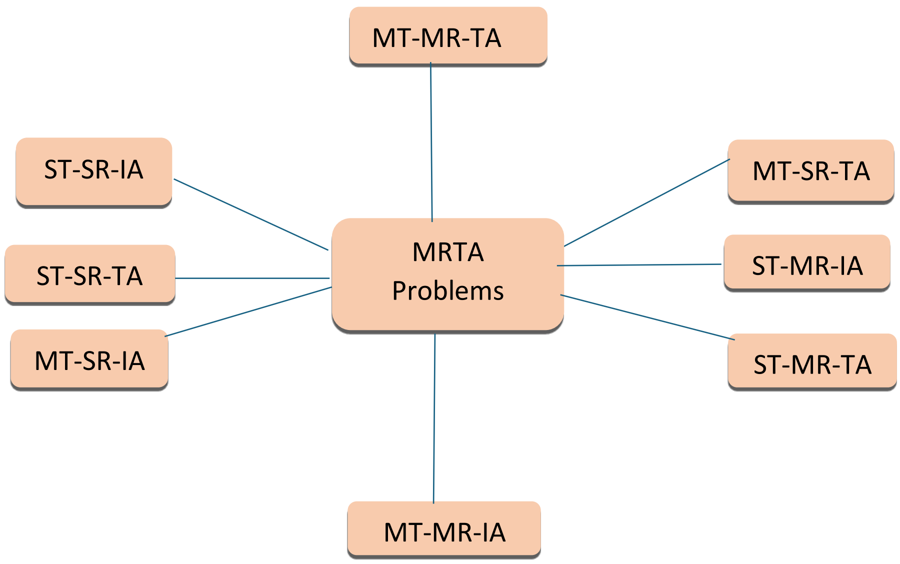


fig 2: Classification of MRTA problems

This classification framework (Figure 2) enables the precise characterization of MRTA problems, facilitating the identification of specific challenges and requirements. For instance, an MT-SR-IA classification denotes a scenario where robots can perform multiple tasks at the same time, each task requires only a single robot, and tasks are allocated instantaneously without regard for future assignments. This taxonomy provides a foundation for distinguishing between eight distinct types of MRTA problems, enriching the discourse on robotic task allocation by offering structured insights into the complexities inherent in diverse operational environments.

OBJECTIVES

Multi-Robot Task Allocation (MRTA) is recognized as a combinatorial optimization challenge, often conceptualized through operations research methodologies that employ mathematical modeling to enhance the functionality of complex systems. This domain encompasses a broad spectrum of disciplines, including artificial intelligence, machine learning, software engineering, applied mathematics, and computer science, to develop sophisticated algorithms for task assignment. The integration of machine learning and artificial intelligence enables the autonomous distribution of tasks among robots, facilitating their capability to learn from previous errors and adjust to evolving operational conditions. Additionally, the principles of software engineering play a critical role in the development process, necessitating a foundation in computer science and application mathematics to devise efficient workflows and to craft the requisite robot control programs. Looked as a subset of discrete-optimization, MRTA deals extensively with graph-based structures, employing mathematical models to navigate the intricacies of the problem space. The essence of combinatorial optimization in this context lies in identifying the optimal solution from a finite set of possibilities, bounded by an objective function within a discrete, extensive search space. Moreover, these solutions must conform to a set of predefined constraints or conditions. To address these challenges, resolution techniques bifurcate into the following principal categories: Approximate and Exact approaches [20].

For example, we have a scenario with 3 robots (R1, R2, R3) and 4 tasks (T1, T2, T3, T4). Each task takes a different amount of time depending on which robot performs it. The aim is to allocate each task to a single robot in a manner that minimizes the overall completion time for all tasks. X$\boldsymbol{ij}$**:** Binary decision variable where Xij=1 if task j is assigned to robot i; otherwise, xij=0.

Given the above definitions, the ILP formulation for this MRTA problem can be written as:

$$\textbf{Minimize} \quad \sum_{\substack{i=1 \\ j=1}}^{\substack{i=3 \\ j=4}} \boldsymbol{x_{ij} \cdot t_{ij}}$$

Subject to:

$$\mathbf{x_{11} + x_{21} + x_{31} = 1; x_{12} + x_{22} + x_{32} = 1; x_{13} + x_{23} + x_{33} = 1; x_{14} + x_{24} + x_{34} = 1}$$

$$x_{ij} \in \{0,1\} \text{ for all I = 1,2,3 and j = =1,2,3,4}$$

Approximate methods offer a viable alternative for addressing large-scale optimization problems where obtaining an optimal solution within a reasonable timeframe is impractical. These methods are particularly beneficial for scenarios demanding real-time solutions to extensive numerical problems. Additionally, they serve as effective preliminary steps in initializing exact methodologies. Approximate methods are broadly categorized into heuristic-based and metaheuristic-based strategies. Heuristics employ simplified decision-making processes or "rules of thumb" derived from empirical evidence to expedite problem-solving. In contrast, metaheuristics approach problem-solving by starting with a set of potential solutions or a indecisively generated or selected preliminary pool of candidates [29]. Through an iterative process, these methods progressively refine the pool of solutions, aiming for gradual improvement. Below is a delineation of predominant approximate methods:

- **Constructive Methods**: The Greedy Algorithm is a quintessential example [21], building a solution piece-by-piece by selecting the most advantageous option at each step with the hope of finding a local optimum.
- **Local-Search Algorithms**: Techniques such as Simulated Annealing (SA) and Tabu Search [22] are pivotal, navigating through the solution space by moving from one solution to a neighboring one, while employing specific mechanisms to escape local optima.
- **Evolutionary Algorithms**: This category encompasses Genetic Algorithms (GA), Grey Wolf Algorihm, Particle Swarm Optimization (PSO), Reptile Search Algorithms (RSA), Ant Colony Optimization (ACO), and Bee Colony Optimization (BCO) [23], all of which simulate natural evolutionary processes or the collective behavior of biological populations to explore and exploit the search space effectively.

Each of these approximate approaches provides a unique strategy for tackling complex optimization problems, offering a balance between solution quality and computational efficiency. These methodologies are instrumental in the realms of operations research and computational intelligence, where they contribute significantly to the advancement of Multi-Robot-Task-Allocation (MRTA) and other optimization challenges.

METHODS

Bio-inspired methods, which mimic biological systems and natural processes, have demonstrated their effectiveness in Multi-Robot Task Allocation (MRTA). These approaches utilize principles from nature to boost both efficiency and adaptability in robotic systems. Several studies [23-28] have implemented heuristic methods to manage task allocation and routing among three robots within a set environment, using Genetic Algorithms (GA) for task assignment and the A* algorithm for central trajectory optimization. Notably, Li et al. [8] enhanced the GA by integrating collision detection and introducing a penalty for collisions, thereby improving the handling of allocation and path planning for multiple robots. Their methodology employs a two-stage process, initially using a constraint k-medoids algorithm for clustering tasks according to robot availability, followed by a GA to fine-tune task allocation and routing while considering energy consumption. Another study [27] demonstrated the effective distribution of tasks across designated sub-regions for environmental exploration, with robots managing tasks within their specific areas using Generalized-Voronoi-Diagram for spatial partitioning, supplemented by Q-learning and GA for optimizing routes.

Moreover, researchers of [6] utilized clustering of k-means to segment environments based on robot availability, assigning robots to these segments and refining their routes with a GA. This approach of partitioning the environment significantly reduces the state space, making it feasible to manage sizable sub-problems rather than a singular, extensive challenge. Kim et al. in [13] explored an decentralized task allocation strategy that employs GA and inter-UAV communication to optimize total flight times and adherence to task sequences.

In the realm of coalition formation for complex tasks, studies [18][19] employed GA to facilitate multi-robot coalition formation. The model in [28] focused on multi-robot coalitions, while [29] adapted this framework to accommodate homogeneous robots engaged in precedence-constrained operations, with the objective function considering travel time, task duration, waiting times for inter-robot cooperation, and delays stemming from precedence restrictions or constraints.

Other bio-inspired algorithms, like Ant Colony Optimization (ACO), Bee Swarm Optimization (BSO), and Particle Swarm Optimization (PSO), have also been applied to MRTA challenges [23, 24]. Comparative studies, such as [21], indicate that while GA often outperforms ACO, it tends to require more time to converge to an optimal solution. These methodologies involve robots starting from random or specified locations and iteratively building solutions based on pheromone trails and heuristic cues, refining these paths until a satisfactory solution is achieved. Additionally, a strategy proposed in [20] combines a greedy algorithm with PSO to optimize task distribution among robots, enhancing system efficiency and shortening the duration of missions.

It is essential to further explore state-of-the-art bio-inspired algorithms to understand how they can enhance coordination, optimization, and task execution in robotic swarms or teams.

- **Honey-Badger Algorithm (HBA):**The Honey-Badger Algorithm is influenced by the bold and clever foraging strategies of the honey badger. In a MRS, this algorithm can be utilized for robust and dynamic task allocation and decision-making processes. The key advantage of HBA is its resilience and adaptability in unpredictable environments for example HBA has been improved for optimized convergence and accuracy in network coverage. Additionally, the study [28] made it suitable for applications where robotic systems must operate under variable conditions and respond to sudden changes effectively.
- **Grey-Wolf Optimizer (GWO):**The Grey Wolf Optimizer draws its inspiration from the social structure and hunting tactics of grey wolves. This algorithm mimics the leadership and team-based hunting approach where the alpha (best solution) guides the pack, and the beta and delta wolves assist in refining the hunt (solution). In multi-robot systems, GWO can optimize the spatial distribution of robots for tasks like area coverage or target tracking, ensuring efficient cooperation and task execution with minimal redundancy and maximal area coverage.[15]
- **Reptile Search Algorithm (RSA):**Drawing inspiration from the adaptive mechanisms of reptiles, the Reptile Search Algorithm focuses on survival tactics such as mimicry, camouflage, and optimized movement patterns. For multi-robot systems, RSA could be particularly useful in applications requiring stealth and energy efficiency, such as surveillance and rescue missions in challenging terrains[9]. The algorithm's efficiency in navigating and adapting to complex environments helps in optimizing routes and strategies with minimal energy consumption.
- **Crow Search Algorithm (CSA):** Based on the intelligent foraging behavior of crows, which store excess food and retrieve it later, the Crow Search Algorithm is used for solving optimization problems[7]. In the context of multi-robot systems, CSA can enhance the retrieval and allocation of resources or navigation to points of interest. Its ability to remember good solutions and explore around these areas can be harnessed to improve the strategic deployment of robots in tasks like harvesting energy sources or collecting environmental data.

- **Firefly Algorithm (FA):** The Firefly Algorithm is inspired by the bioluminescent communication of fireflies. This algorithm uses the concept of attractiveness proportional to brightness to form a basis for attraction among agents. In multi-robot systems, FA can be applied to problems where the objective is to converge towards the best solution through cooperative behavior [10]. This could include synchronization tasks, formation control, or optimization of sensor networks where each robot adjusts its position relative to the performance (brightness) of its neighbors.

RESULTS

Each algorithm brings unique strengths to multi-robot systems. The choice of algorithm should be influenced by the specific operational requirements and environmental conditions. For instance, HBA and FA are preferable in dynamic and unpredictable environments, while GWO and CSA might excel in scenarios that benefit from structured approaches and strategic planning. RSA is particularly suited for physically demanding tasks where environmental adaptability is crucial. The Table 1 below compares these algorithms across several key metrics relevant to multi-robot systems.

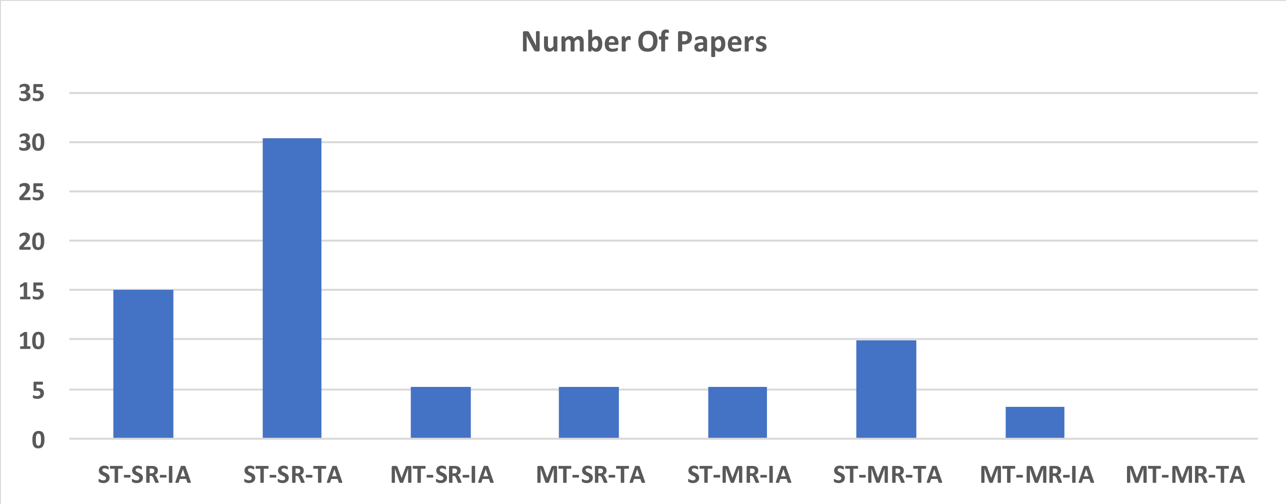
Criterion	Honey-Badger Algorithm (HBA)	Grey-Wolf Optimizer (GWO)	Reptile-Search Algorithm (RSA)	Crow-Search Algorithm (CSA)	Firefly Algorithm (FA)
Adaptability	High (dynamic environments)	Moderate (structured environments)	High (physically challenging environments)	Good (experience-based learning)	Excellent (local interactions)
Scalability	Good (challenges in very large swarms)	High (clear hierarchical roles)	Moderate (small-group focus)	Very high (experience sharing)	Extremely high (simple local rules)
Robustness	Very high (handles failures well)	Moderate (depends on hierarchy stability)	High (effective in harsh environments)	Good (strategic recovery capability)	High (handles performance fluctuations)
Communication Overhead	High (needs coordination)	Moderate to high (hierarchical communication)	Low to moderate (focus on individual adaptability)	Moderate (information sharing about experiences)	Moderate (needs constant local management)
Efficiency	High (quick, decisive actions)	Efficient (task-specific structuring)	High (balances exploration and exploitation)	Variable (environment-specific)	Very high (converges quickly)

Table 1: Key Algorithms across several key metrics of MRS

The integration of advanced architectures and communication strategies, coupled with the exploration of practical applications and the navigation of inherent challenges, establishes a comprehensive foundation for understanding this dynamic and evolving field of research, The architecture of multi-robot systems (MRS) exhibits a complexity that is integral to their function and efficacy in various operational environments. Typically, the MRS architecture can be categorized as hierarchical, comprising an amalgamation of hardware and software components that facilitate both functionality and interoperability[6]. At the core of each individual robot lies an assembly of essential elements, including sensors that gather environmental data, actuators that execute movement or operational tasks, and a processing unit that interprets the data and makes decisions based on pre-defined algorithms. These components work in concert with a central control system, which plays a crucial role in managing task distribution and fostering cooperation among robots [7].

DISCUSSION

While the applications of multi-robot systems are varied and beneficial across multiple domains, addressing the inherent challenges of coordination, communication, and performance is crucial for maximizing their potential. The ongoing research aimed at overcoming these obstacles will shape the future prospects of MRS in numerous fields, further solidifying their role in advancing technology and societal needs., The complexities of coordination and collaboration among multi-robot systems (MRS) stem from diverse operational environments and the necessity for synchronous interaction among heterogeneous agents. Task allocation often embodies a significant challenge, as the effective distribution of tasks relies on both the capabilities of individual robots and the overarching mission goals. Figure 3 displays the distribution of research articles across various MRTA problem categories, with the Multi Robot Task Allocation(MRTA) problem configurations organized on X-axis in increasing order of complexity.



MRTA category

Fig 3: Quantitative Analysis of Research Papers Based on Problem Configuration.

The dynamic nature of many real-world scenarios exacerbates this complexity, demanding that robots adapt their roles in response to changing conditions. Consequently, algorithms for task allocation must not only consider optimal performance criteria but also factor in constraints related to communication delays and resource availability. In conclusion, addressing these specified challenges is essential for the experimental validation of developed algorithms and for progressing in the field of mobile robotics. This paper calls for a concerted effort to integrate and test MRTA solutions under more realistic conditions, thereby bridging the gap between theoretical research and practical implementation. As highlighted [31], new distributed optimization techniques hold promise for enhancing coordination in uncertain environments. These methods enable robots to exchange information and adjust their strategies dynamically, allowing for resilient and robust team performance. Heterogeneity in robot capabilities paves the way for additional coordination challenges. Multi-robot systems often comprise robots with varying levels of sensing, processing, and actuation abilities. This diversity, while advantageous in many ways, necessitates sophisticated coordination frameworks to harmonize the actions of dissimilar agents and exploit their unique strengths.

QUANTUM COMPUTING IN MULTI ROBOT SYSTEMS

The integration of quantum computing in swarm robotics is still in its early stages. However, there have been several promising developments in this area. One notable example is the use of quantum annealing to solve optimization problems in swarm robotics. Quantum annealing is a technique that utilizes the quantum mechanical phenomenon of tunneling to find the lowest energy state of a system. This can be applied to swarm robotics by using it to optimize task allocation and path planning algorithms. Applications of quantum computing to swarm robotics concerns collaborative robotic tasks of autonomous robots (unmanned) as parts of a network whose agents are entangled [34]. The potential advantages of quantum-based cooperation of agents embodied in interacting robots deal with security against quantum attacks, thanks to entanglement, which constitutes a chapter of quantum mechanics in itself. It is proved that entanglement leads to the improvement of the collaborative behaviour of the robotic equivalent of ants . Quantum computing is also helpful in the domain of optimization. A set of multiple, interacting robots can reach their target through swarm evolution mechanisms, and such a strategy is improved via a quantum-based optimization algorithm, jointly with a collision/obstacle avoidance scheme [35]. Another area of research is the use of quantum algorithms to improve the efficiency of data processing in swarm robotics. For example, the use of Grover's algorithm can improve the speed of searching for a specific item in a large dataset. This can be applied to swarm robotics by improving the ability to detect and track objects.

Several studies have explored the use of quantum computing in swarm robotics. For example, a recent study [32] proposed a quantum-inspired algorithm for task allocation in swarm robotics. The algorithm uses quantum annealing to solve the task allocation problem, which is a combinatorial optimization problem. The algorithm was tested on a swarm of robots, and the results showed that it outperformed classical algorithms in terms of task allocation efficiency. Another study [33] proposed a quantum-inspired algorithm for task allocation in multi robot systems. The algorithm uses quantum walks to find the optimal path for a swarm of robots. The algorithm was tested on a simulated swarm of robots, and the results showed that it outperformed classical algorithms in terms of path planning efficiency. Despite the potential benefits of quantum computing in swarm robotics, there are several challenges associated with its use. One of the main challenges is the hardware limitations of quantum computing. Quantum computers are still in their early stages of development, and their hardware is not yet mature enough to support complex swarm robotics algorithms. Quantum computing requires a different programming paradigm than classical computing, which can make it difficult for developers to write efficient quantum algorithms. The quantum paradigm also helps improve learning approaches; quantum-enhanced clustering algorithms and deep self-learning approaches have been used to improve swarm intelligence algorithms, and for emergency vehicle dispatch management during the COVID-19 crisis [36].

There is also a shortage of skilled quantum computing professionals, which can limit the adoption of quantum computing in swarm robotics.Another challenge is the development of algorithms that are specifically tailored for quantum computing. Many of the existing algorithms used in swarm robotics were designed for classical computing and may not be optimized for quantum computing. However, researchers are actively developing new algorithms that are designed to take advantage of the unique properties of quantum computing. Despite these challenges, the integration of quantum computing in swarm robotics has significant future opportunities. The improved computational power offered by quantum computing can lead to more efficient and effective swarm robotics systems. This can have applications in various fields, including agriculture, search and rescue, and military.

CONCLUSION

In conclusion, the integration of quantum computing into swarm-based multi-robot systems holds the promise of transforming how complex tasks are approached and executed. As both quantum technologies and robotic systems continue to evolve, their convergence is anticipated to lead to more intelligent, efficient, and adaptable robotic swarms capable of addressing a wide array of real-world challenges. Optimization related approaches and methods in Multi Robot Task Allocation (MRTA), offering a global perspective on the various optimization strategies applicable to different problem classes and real-world scenarios. A detailed quantitative analysis of selected papers underscores the prevailing focus within the research community on Single Task Single Robot with Time Allocation (ST-SR-TA) problems. Our paper highlights a significant gap in the literature concerning the numerical complexity of algorithms, with only a limited exploration of online assignment strategies for dynamic environments. Additionally, performance enhancements are often achieved through hybrid approaches that either refine approximate solutions or partition the problem into discrete phases of task assignment and task planning.The Honey badger algorithm and reptile search algorithm emerges as the predominant recent methods in this area, and it is noted that many studies do not specify particular applications, reflecting a broader applicability of the proposed methodologies.In summary, overcoming the challenges inherent in coordination and collaboration among multi-robot systems is essential for maximizing their effectiveness across various applications. Addressing task allocation, resource sharing, uncertainty management, and communication strategies, while also considering the impacts of heterogeneous capabilities, plays a crucial role in the advancement of MRS technology with quantum computing. This paper calls for a concerted effort to integrate and test MRTA solutions under more realistic conditions, thereby bridging the gap between theoretical research and practical implementation. To overcome the challenges associated with quantum computing, there is a need for further research in several areas. One area of research is the development of quantum hardware that is specifically designed for swarm robotics. This can include the development of specialized quantum processors and sensors that are optimized for swarm robotics algorithms. Another area of research is the development of programming tools and frameworks that simplify the development of quantum algorithms for swarm robotics. This can include the development of high-level programming languages and libraries that abstract away the complexity of quantum programming.

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