Reinforcement Algorithm for Energy Harvesting & Task Allocation in Multi-Robot systems

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Abstract: Mental health disorders have emerged as one of the most formidable challenges of the 21st century, affecting nearly 970 million individuals worldwide [1], [2]. With the rapid advancement of artificial intelligence (AI) technologies, researchers and clinicians are increasingly harnessing these tools to enhance diagnostic accuracy, personalize therapeutic interventions, and expand access to mental health services [3], [4]. This review paper critically examines current AI-based tools that are transforming mental health care. In particular, we analyze machine learning algorithms, deep learning architectures, and natural language processing (NLP) applications in psychiatric diagnostics and therapy. Our analysis draws upon recent studies and meta-analyses to present data-driven insights, illustrated with sample graphs and statistical findings. Moreover, ethical, privacy, and implementation challenges are discussed alongside future directions for integrating AI into mental health systems. Our review not only synthesizes the state-of-the-art research but also outlines a roadmap for future studies, ensuring that AI becomes a trusted partner in mental health care [5]–[8].

Keywords: Machine Learning (ML), Artificial Learning (AI), Natural Language Processing (NLP), Mental Health Disorder.

1. Introduction

The undertaking problem in multi-robot structures (MRTA) involves distributing tasks among robots to obtain goals together with minimizing time, enhancing performance, or optimizing energy use. With robots increasingly more hired in sectors like manufacturing, surveillance, and logistics, powerful venture venture is critical. Traditional methods warfare with scalability and adaptability, especially in dynamic or unpredictable environments as robot structures become extra complex, progressive strategies are required to manipulate them correctly. Recent improvements in device getting to know, specifically reinforcement learning (RL), present promising answers. Multi-robot structures are pivotal in automating large-scale and excessive-threat operations at some point of numerous domains. These structures are deployed for responsibilities together with are searching out and rescue missions, warehouse automation, environmental tracking, and military reconnaissance. Collaborative robotic companies can acquire ordinary performance and reliability in situations in which unmarried robots fall quick. For example, in disaster reaction, multiple robots can simultaneously perform reconnaissance, particles clearing, and sufferer assistance. Similarly, self sufficient drones can collaboratively survey big regions effectively. These numerous packages underline the need for effective project allocation strategies to maximize system stylish average universal performance.

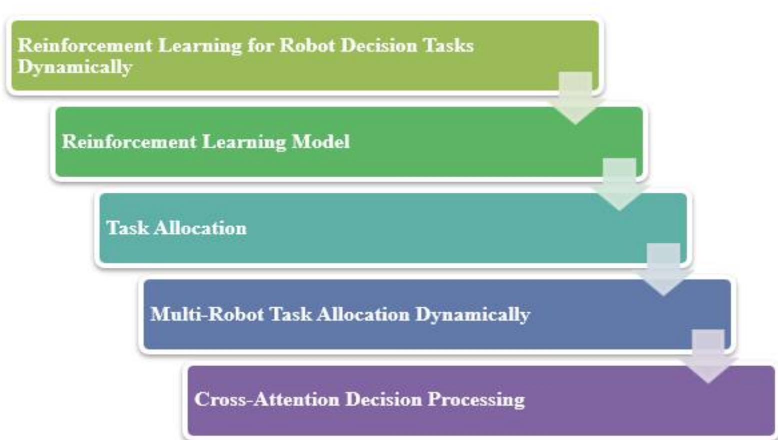

Fig 1: Multi-Robot Systems and Their Applications

Allocating responsibilities to robots in multi-robot systems is an NP-hard problem due to the exponential growth in challenge possibilities. This complexity is compounded via factors like challenge dependencies, energy constraints, and real-time operational requirements. Additionally, dynamic environments with unpredictable variables make static allocation techniques insufficient.[6] Achieving great average performance requires addressing competing desires, which embody minimizing time at the same time as holding electricity. Scalability stays a prime problem, as modern-day algorithms falter at the same time as coping with huge robot networks. Developing strategies that adapt to converting situations on the identical time as making sure computational general normal performance is important for contemporary-day programs [1].Classical MRTA methods embody techniques like integer-linear programming, public sale-based totally absolutely algorithms, and graph-based absolutely strategies. These strategies were effective for solving small-scale allocation issues in managed environments. Integer-linear programming gives specific solutions however are computationally big for huge structures. Auction-based totally clearly algorithms offer faster answers however may additionally sacrifice optimality. Graph-primarily based techniques are suitable for spatial undertaking allocation but war with dynamic assignment requirements. While those techniques laid the basis for MRTA, they lack the electricity to address the growing complexity and scale of present day multi-robotic systems. Reinforcement learning (RL) affords an adaptive framework for fixing MRTA troubles via getting to know premier regulations thru environment interaction. Unlike supervised mastering, RL does not depend upon labeled records, making it greater applicable to dynamic, real-world scenarios. RL-primarily based techniques have proven fulfillment in combinatorial optimization issues like the TSP and vehicle routing hassle (VRP). These methods research from exploration and modify strategies based totally on environmental comments. By incorporating multi-agent RL strategies, MRTA systems can dynamically allocate responsibilities in actual-time even as adapting to aid constraints and undertaking variability [3]. This framework introduces an RL-primarily based framework for MRTA, addressing the demanding situations of multi-robotic and multi-project scenarios. The problem is modeled as a Markov Decision Process (MDP) to permit powerful coverage studying. A dot-product go-interest mechanism courses the allocation system, emphasizing the importance of particular responsibilities to robots. The framework is optimized the usage of a coverage gradient technique with a greedy baseline, making sure sample performance. By integrating those additives, the proposed approach achieves scalability and interpretability, making it suitable for complicated, large-scale allocation issues. The proposed RL-based MRTA technique become evaluated in various mission allocation scenarios, demonstrating superior overall performance over conventional meta-heuristic baselines. It efficiently minimized total venture final touch time and treated scalability in massive robot networks. Additionally, the eye mechanism provided interpretability through highlighting venture priorities. Key contributions include an MDP-primarily based allocation set of rules and an RL version structure tailored for complex MRTA problems [4]. This work establishes a robust, green, and scalable method to multi-robot project allocation, paving the way for superior packages in dynamic environments.

2. Literature Review

In recent years, there has been growing literature on the multi-robot task-allocation problem. In this section, we survey the recent papers in the MRTA literature.

The authors in [18] considered the simplest version of the multi-robot task-allocation (MRTA) problem in a multi-robot system and propose an optimal centralized solution, the Hungarian method. Despite its optimality, this kind of solution has the typical drawbacks of the centralized approach. For example, they show very slow responses to dynamic changes. Therefore, more distributed algorithms are proposed for this problem.

The authors in [17] considered an MRTA problem. An auction-based method is proposed for the task allocation to a group of robots. Tasks are considered to be some locations that the robots need to visit. A robot may be prevented from completing its allocated tasks using unexpected obstacles and delays. Therefore, the uncompleted tasks are rebid every time a robot completes its (previously) assigned task. This provides an opportunity to improve the allocation of the remaining tasks and to reduce the overall task-completion time.

The authors in [16] handled a MRTA problem in a multi-agent system. In this problem, there are tasks and identical agents where the number of tasks is less than the number of agents. Using distributed control laws, the agents are split into groups, each of which is assigned to a task. The paper suggests a distributed market-based solution. In the system, each agent has the information on all tasks and the maximum number of agents that can be assigned to each task. By considering the availability of the requested tasks, these agents communicate with each other to compare the bids and thus this knowledge propagates over the network. The authors in [14] studied an initial formation problem in robotic swarm. Its goal is to minimize a certain objective function by determining which robot should go to each of the formation positions. The authors proposed an algorithm named Robot and Task Mean Allocation algorithm. In this algorithm, the cost is considered to be the difference between the distance from the robot to the task and the mean of distances from all the robots to that task. As a result, the robot will win the task that is best for the team, not only for itself.

Centralized techniques for MRTA, which incorporates the Hungarian set of guidelines, offer gold trendy answers for easy project allocation issues. These strategies assume a unmarried controller that possesses international know-how of the system and might allocate duties to robots efficaciously. However, centralized strategies face limitations in scalability and adaptableness, particularly in dynamic environments. For instance, they exhibit sluggish responses to sudden activities, along with robot screw ups or challenge interruptions. Despite their drawbacks, centralized solutions offer a foundational framework for know-how assignment allocation issues and are nonetheless relevant for small-scale systems. Auction-based totally completely absolutely methods have acquired reputation for his or her allotted and flexible nature in MRTA [11]. Robots bid for duties based completely totally on software program values, allowing dynamic undertaking allocation as conditions alternate. For instance, techniques regarding rebidding enhance commonplace overall normal overall performance via the usage of manner of reallocating uncompleted obligations because of barriers or delays. Market-primarily based absolutely techniques increase this concept thru manner of allowing robots to change statistics about undertaking necessities and their availability. These strategies strike stability among centralization and decentralization, making them powerful for environments with mild complexity. Distributed techniques are crucial for big-scale or swarm robotic systems, in which essential coordination is impractical. In those algorithms, every robot operates primarily based totally on close by know-how and communicates with buddies to acquire a collective selection [12]. MRTA troubles often contain duties with unique time limits or grouped necessities. For instance, responsibilities also can require more than one robot to collaborate within a constrained time-body. Luo et al. addressed this by using manner of the use of thinking about overlapping assignment organizations with ultimate date constraints, enabling inexperienced multi-robot collaboration. Similarly, situations with disjoint undertaking companies require algorithms that make certain maximum payoff at the same time as respecting robotic capacities and challenge time limits. These strategies are critical for applications like catastrophe reaction, wherein timing and coordination are important. Decentralized MRTA techniques leverage ideas like sub modularity to simplify complex allocation troubles. Submodular optimization provides theoretical ensures for answer satisfactory even as decreasing computational complexity. For instance, sampling-based techniques ensure close to-optimum answers for monotone and nonmonotone submodular instances. These techniques reveal comparable or advanced overall performance to ultra-modern algorithms, especially for massive-scale systems. By addressing combinatorial complexity with decentralized choice-making, submodular optimization expands the applicability of MRTA to various, computationally in-depth situations. Robot group coordination is critical for green undertaking of entirety in multi-robot systems. The SQ-MRTA algorithm enables robots to dynamically allocate responsibilities and collaborate seamlessly. Tasks T1 and T2, representing particular tasks in the system, spotlight the want for synchronized efforts among robots. Each robotic shares its repute and progress, making sure minimum delays and green assignment of completion. This technique guarantees ideal aid utilization, particularly in dynamic environments with various task priorities. Future improvements ought to enhance coordination with the aid of incorporating actual-time remarks and adapting to bodily constraints.

Table 1. The first set of numerical experiments with robot teams**.**

Teams	No. of Robots	No. of Teams	No. of Goals	Length
T 1T 1	73	9	73	38.43
T 2T 2	50	10	2	42.01
T 3T 3	45	11	45	13.18
T 4T 4	42	33	42	6.03
T 5T 5	75	49	22	68.46

➢ **Error Simulation and Noise Consideration:** To make the simulation greater practical, we introduced sensor and conversation noise into the device. The IR sensors on the Corobot had 5% mistakes for readings between 0.1 and 0.8 meters and as much as 50% blunders for stages beyond 0.8 meters.

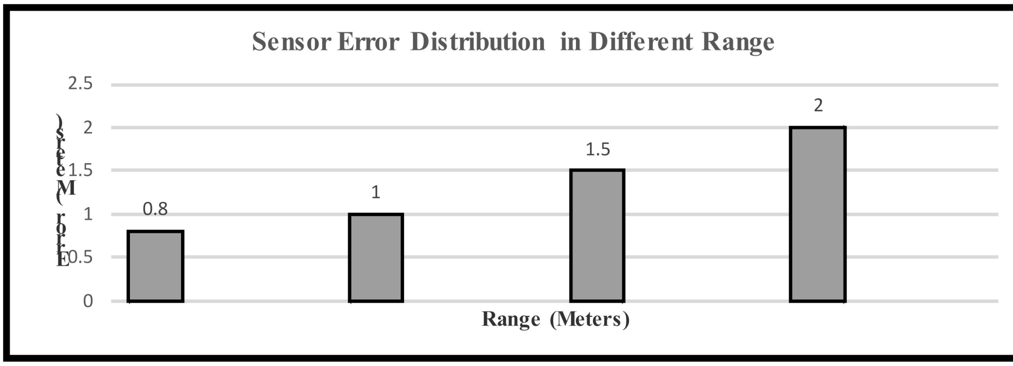

Fig 2: Sensor Error Distribution in Different Range

➢ **Comparative Analysis with Other Algorithms:** In order to evaluate the effectiveness of the SQ-MRTA set of rules, it changed into in comparison with several traditional and heuristic-based totally algorithms. The effects validated that SQ-MRTA outperformed the opposite strategies in terms of time efficiency, with robots completing obligations greater fast and with fewer interruptions. This become in particular evident in dynamic challenge allocation situations where responsibilities had been delivered or altered all through the simulation. In comparison, conventional algorithms struggled with actual-time mission reassignment and coordination [5].The evaluation of challenge allocation revealed that the SQ-MRTA set of rules become instead powerful in balancing the load amongst robots. By thinking about factors inclusive of robotic position, assignment requirements, and communication constraints, the set of rules minimized idle time and ensured that robots have been evenly dispensed throughout duties. The challenge allocation turned into dynamic, considering actual-time adjustments primarily based on assignment crowning glory and robotic availability. This dynamic approach extensively decreased the general final touch time as compared to static allocation strategies. The results of the simulation indicated that the SQ-MRTA algorithm successfully minimized the overall assignment finishing touch time, with the robots strolling in a in particular coordinated way. The time required to navigate among obligations emerge as appreciably decreased, manner to the set of rules's functionality to optimize undertaking sequencing. In conditions related to sensor noise and verbal exchange delays, the SQ-MRTA set of policies showed resilience, maintaining excessive degrees of performance even underneath imperfect situations. Overall, the findings propose that SQ-MRTA provides a scalable and effective answer for multi-robot task allocation in complicated environments.

4. Challenges & Future Directions

The conversation network is modeled as a completely connected graph, wherein robots are nodes, and hyperlinks represent inter-robot conversation. This topology, with a redundancy level of m−1, guarantees excessive robustness and resilience in opposition to communique disasters that is vital for dynamic environments. The conversation value for undertaking allocation is analyzed the use of an public sale-based totally mechanism, wherein robots act as bidders and responsibilities as gadgets to be allocated. The set of rules minimizes conversation overhead with the aid of dynamically adjusting venture allocation as responsibilities are finished, improving standard efficiency and scalability. By employing demand query mechanisms, the SQ-MRTA algorithm extensively reduces verbal exchange overhead as compared to conventional auction models [5]. This development permits the gadget to operate effectively at the same time as the range of robots and obligations will increase. The algorithm's potential to balance conversation costs and task allocation performance demonstrates sturdy scalability for large structures [4]. The fully related network ensures robustness but may additionally cause better preliminary communique infrastructure expenses. Balancing redundancy and efficiency stay an important realistic consideration.

➢ Despite the found performance, real-global elements inclusive of latency, packet loss, and dynamic venture arrivals pose challenges that want to be addressed.

➢ Future enhancements should include adaptive conversation techniques and mechanisms to handle dynamic environmental situations extra efficiently.

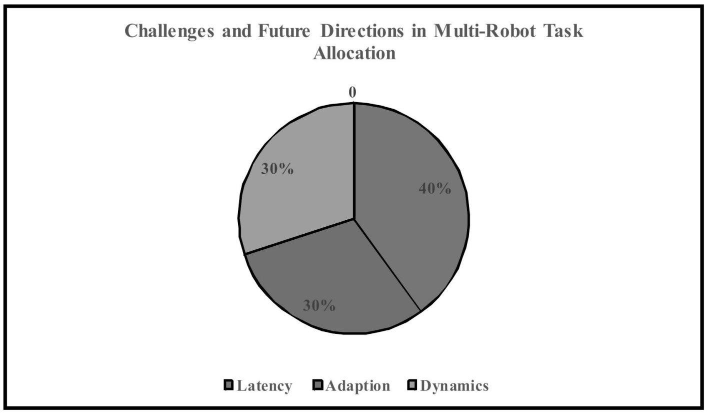

Fig 3: Challenges and Future Directions in Multi-Robot Task Allocation

The SQ-MRTA set of rules offers a robust and efficient framework for undertaking allocation in multi-roboticstructures by way of optimizing communication prices even as ensuring resilience. Its scalability and robust performance make it properly-proper for real-international packages. However, similarly refinements are necessary to deal with sensible challenges in dynamic and huge-scale environments.

5. Conclusion

The project allocation hassle in multi-robot structures is important for optimizing the distribution of responsibilities to enhance normal overall performance and restrict completion times. In this look at, we added the Spatial Queuing-Multi Robot Task Allocation (SQ-MRTA) set of guidelines and evaluated its overall performance using simulations of Corobot robots in dynamic environments. The SQ-MRTA set of rules tested robust typical performance throughout various situations, effectively balancing assignment allocation and lowering navigation instances. When in comparison to present algorithms which encompass the Hungarian approach, grasping allocation, and repeated auctions, SQ-MRTA exhibited superior adaptability, especially in real-global environments wherein elements like undertaking delays and collision avoidance considerably effect universal performance. Unlike offline nice schedules, our set of regulations is able to handling dynamic project arrivals and communication constraints. Future research will increase this work to physical robots, addressing demanding situations along with sensor inaccuracies and conversation noise. Moreover, incorporating heterogeneous robots with numerous skills, task prioritization, and temporal constraints ought to similarly decorate its software in complex domain names like landmine detection, searching for-and-rescue, and commercial enterprise operations. This look at underscores the ability of adaptive, decentralized techniques for strong and green multi-robotic challenge allocation.

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