Implementation of Decentralized Coordination for Spatial Task Allocation and Scheduling in Heterogeneous Teams on real robots

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***Abstract*—In the context of coordination and planning in collaborative multi-robot/agent systems, we consider a general reference problem that includes tasks that are spatially localized and have an associated service time, and accounts for the use of a heterogeneous team, in which different robots may have a different performance on the same task. A mixed integer linear formulation is used to solve the problem of decentralization, aiming to find the adapatbility of the formulation on real robots [1]. The approach is verified on the robots and results are presented. Gazebo simulator is being used for testing the mathematical approach on multi-agents.**

I. Introduction

It is well understood that, in general, the support of a coordinated planning scheme is necessary to optimize the performance of a multi-agent team [1]. Coordination is required to avoid conflicts, unnecessary overlapping, and incoherent executions, while, at the same time, to boost cooperation and synergies when tackling a common mission. This is even more true when the team is heterogeneous, due to the fact that different agents might perform differently for the various sub-tasks composing the overall mission. In this work, we focus on mission scenarios that require the use of embedded physical agents, a mobile multi-robot team in particular, and that are defined through a set of spatially distributed tasks, each with its own characteristics and demand levels. The class of problems that we consider generalizes the classical multi-robot task allocation problems. The problem is referred by the authors as the spatial task allocation and scheduling problem in heterogeneous multi-robot teams, or STASP-HMR in short. The authors proposed a decentralized approach for STASP-HMR, where each agent runs a replica of the mathematical model, based on local data and limited information sharing. Apart from the characterization of the above class of problems, our contribution here is two-fold. First, they introduced a decentralized coordination and planning algorithm that meets computational and communication requirements, and at the same time incurs in limited performance losses compared to the centralized solution. Second, they proposed a general top-down recipe for deriving an effective decentralized scheme from a centralized mathematical model. Our goal to implement STASP-HMR approach on real robots and compare results of the both centralized and decentralized approaches [1].

II. Related Work

Plan monitoring in a collaborative multi-agent system requires an agent to not only monitor the execution of its own plan, but also detect the possible deviations or failures in plan execution of its teammate. They designed an Expectation Maximiztion (EM) based algorithm for detection of plan deviation of agents in a multi-agent system [3]. In my paper I tackle the problem of coordination and planning in collaborative multi-robot/agent systems using top-down recipe for decentralization, aiming to balance the tradeoff among implementation costs, computational requirements, and quality of coordination.

This paper addresses task allocation to coordinate a fleet of autonomous vehicles by presenting two decentralized algorithms: the consensus based auction algorithm (CBAA) and its generalization to the multi-assignment problem, i.e., the consensus-based bundle algorithm (CBBA) [4]. From the above paper I understood how they are doing conflict-free assignment of tasks to multi-agent tea. This can be an alternative approach to Mixed linear formulation approach.

Although multi-robot systems have received substantial research attention in recent years, multi-robot coordination still remains a difficult task. Especially, when dealing with spatially distributed tasks and many robots, central control quickly becomes infeasible due to the exponential explosion in the number of joint actions and states. The authors proposed a general algorithm that allows for distributed control, that overcomes the exponential growth in the number of joint actions by aggregating the effect of other agents in the system into a probabilistic model, called subjective approximations, and then choosing the best response. They showed for a multi-robot grid world how the algorithm can be implemented in the well studied Multiagent Markov Decision Process framework, as a sub-class called spatial task allocation problems (SPTAPs) [5].

From the above paper I understood that how spatial tasks can be allocated to multi-agents using Markov Decision Process framework .This algorithm can be used as an alternative approach to allocating tasks to robots through mixed integer linear program approach.

(AUTOMATIC target recognition ATR) involves determining the visual and other distinguishing features of an object, which is usually from a distance, and using this signature to automatically identify the object as a potential target. For many current applications,ATR is performed by unmanned aerial vehicles (UAVs) that fly within a reconnaissance area to collect image data through sensors and upload the data to a central ground control station for analyzing and identifying potential targets. The centralized approach to ATR introduces several problems, including scalability with the number of UAVs, network delays in communicating with the central location, and the susceptibility of the system to malicious attacks on the central location. These challenges can be addressed by using a distributed system for performing ATR [6]. In this paper, the authors described a multiagent-based prototype system that uses swarming techniques inspired from insect colonies to perform ATR using UAVs in a distributed manner within simulated scenarios. From the above paper I understood how multi-agent based systems can be used for AUTOMATIC target recognition ATR).

In this paper a novel decentralized approach for task sequencing within a multiple missions control framework is presented. The main contribution of this work concerns the decentralization of a control framework for multiple mission execution in order to enhance the robustness of the system, and the application of the latter to a heterogeneous robotic network. The proposed approach is based on the Matrix based Discrete Event Framework (MDEF) [7].

From the above paper I understood decentralization of a control framework for multiple mission execution in order to enhance the robustness of the system, and the application of the latter to a heterogeneous RN.

A mixed integer linear formulation is introduced and used to solve the problem model in a centralized iterative manner in closed loop, team-level plans are adaptively computed and sent out. Unfortunately, a centralized scheme can suffer from computational and communication shortcomings. Therefore, we introduce a top-down recipe for decentralization, aiming to balance the tradeoff among implementation costs, computational requirements, and quality of coordination [1].

I am replicating the work done by the authors in the above paper. The authors have shown the results by study through an empirical sensitivity analysis, but did not test the algorithm on any robots. We intend to see the results of the algorithm using real robots.

The authors presented a mixed linear formulation for mission planning in heterogeneous teams of physical agent. The targeted missions can be composed of set of spatially distributed task. The aim of mathematical formulation is to assign plans to agents by exploiting their specific characteristics in relation to the tasks,promoting their synergies. The authors included in the formulation a number of different aspects derived from real-world mission planning scenarios, which include the ability to enforce spatial-temperoral relations among groups of agents,dealing in a robust way with uncertainty in plan execution,letting open the possibility to complete a task incrementally,by different agents in different times. As a result the model is highly realistic and flexible. we also presented a computationally effective solution approach,that preserves some optimality guarantees while saving computations [2].

The above paper is the initial work done by the authors using mixed linear formulation for mission planning as centralized approach in heterogeneous teams of physical agents. I have also got the idea for the experimental setup from this paper.

Coverage Path Planning (CPP) is the task of determining a path that passes over all points of an area or volume of interest while avoiding obstacles. This task is integral to many robotic applications, such as vacuum cleaning robots, painter robots, autonomous underwater vehicles creating image mosaics, demining robots, lawn mowers, automated harvesters, window cleaners and inspection of complex structures, just to name a few. This work aims to become a starting point for researchers who are initiating their endeavors in CPP. Likewise, this work aims to present a comprehensive review of the recent breakthroughs in the field, providing links to the most interesting and successful works [8].

From the above paper I understood how coverage path planning can be used to determine the paths for multi-agents in various scenarios.

In this paper authors presented a decisional architecture and the associated algorithms for multi-UAV (Unmanned Aerial Vehicle) systems. The architecture enables different schemes of decision distribution in the system, depending on the available decision making capabilities of the UAVs and on the operational constraints related to the tasks to achieve. The decisional autonomy is of 5 levels which consists of both centralized and distributed decision. The paper mainly focuses on the deliberative layer of the UAVs. The authors detailed a planning scheme where a symbolic planner relies on refinement tools that exploit UAVs and environment models. Integration effort related to decisional features is highlighted, and preliminary simulation results are provided [9].

From the above paper I understood how decisional architectures can be used for multi-uav (Unmanned Aerial vehicle) Systems.

This work presents a complete multi robot solution for signal searching tasks in large outdoor scenarios. An evaluation of two different coverage path-planning strategies according to field size and shape is presented. A signal location system developed to simulate mines or chemical source detections is also described. The solution presented is a pioneer in evaluating multi master robotics operative system architectures with a fleet of robots in real scenarios. This solution minimizes the use of communications bandwidth required for full operation. Finally, field results are provided, and the advantages of the implemented solution are analyzed [10].

From the above I learnt how resented system integrates two different coverage path-planning approaches into a software, hardware, and communications architecture and how the system was able to successfully cover the whole area, and to detect all of the signal sources in the field, using both single and multiple robot systems.

The authors proposed an online algorithm that scales linearly in the number of robots and allows for arbitrary periodic connectivity constraints. To complement the proposed algorithm, they provided theoretical inapproximability results for connectivity-constrained planning. It was shown in the non-adversarial search domain that periodic connectivity leads to improved capture times versus continual connectivity. In addition, it was demonstrated that market-based approaches that explicitly coordinate perform only marginally better than implicit coordination, even given significantly more computational time. This paper has provided formal inapproximability results for connectivity constrained multi robot planning with periodic connectivity. Their theoretical analysis has shown that many multi robot coordination problems subject to connectivity constraints cannot be approximated with an efficient algorithm (unless P = N P) [11].

Through this paper I learnt how connectivity-constrained planning can be implemented in different scenarios such as search and rescue missions.

The authors work in this paper focuses on multi-agent coordination for disaster response with intra-path precedence constraints, a compelling application that is not well addressed by current coordination method. This work presents two methods for generating time-extended coordination solutionssolutions where more than one task is assigned to each agentfor domains with intra-path constraints.The first approach uses tiered auctions and two heuristic techniques, clustering and opportunistic path planning, to perform a bounded search of possible time-extended schedules and allocations.The second method uses a centralized, non-heuristic, genetic algorithm-based approach that provides higher quality solutions but at substantially greater computational cost. We compare our time-extended approaches with a range of single task allocation approaches in a simulated disaster response domain [12].

From the above I learnt how multi-agent coordination can be done using heuristic techniques and genetic algorithm-based approach that provides higher quality solutions but at substantially greater computational cost.

In this paper the optimal timing of air-to-ground tasks is considered. A scenario is examined, where multiple unmanned air vehicles (UAVs) must perform one or more tasks on a set of geographically dispersed targets in the presence of no-fly zones. Four different solutions to the UAV assignment problems have been evaluated and compared. Overall, the SA(Simulated Annealing) algorithm gives the best solutions and also shows the largest computation times [13].

In the above paper the authors have used MILP(Mixed integer Linear Programming) as one of the four algorithms for the optimal task assignment.

This paper deals with the task allocation problem in multi-robot systems. The authors proposed a completely distributed architecture, where robots dynamically allocate their tasks while they are building their plans. They kept focus on the problem of simple goto tasks allocation. The approach involves an incremental task allocation algorithm based on the Contract-Net protocol. We introduce a parameter called equity coefficient in order to equilibrate the workload between the different robots and to control the triggering of the auction process. Then, they addressed the problem raised by temporal constraints between tasks, by dynamically specifying temporary hierarchies among the tasks [14].

From the above paper I understood how task allocation problem in multi-robot systems is tackled in the earlier years.

This paper presents the architecture developed in the framework of the AWARE project for the autonomous distributed cooperation between unmanned aerial vehicles (UAVs), wireless sensor/actuator networks, and ground camera network. The architecture is endowed with different modules that solve the usual problems that arise during the execution of multi-purpose missions, such as task allocation, conflict resolution, task decomposition, and sensor data fusion. The approach had to satisfy two main requirements: robustness for operation in disaster management scenarios and easy integration of different autonomous vehicles.The former specification led to a distributed design, and the latter was tackled by imposing several requirements on the execution capabilities of the vehicles to be integrated in the platfor.The experiments with real UAVs presented in the paper have shown that the developed architecture allows coverage of a good spectrum of missions: surveillance, sensor deployment, and fire confirmation and extinguishing. One of the key features of the architecture was the easy integration process of autonomous vehicles from different manufacturers and research groups [15].

From the above paper I understood a different way of task-allocation and execution on muti-agents for multipurpose missions.

Swarm-based systems have emerged as an attractive paradigm for implementing distributed autonomous systems for various applications in commercial, military and business domains. One of the major operations in a swarm-based system is to ensure that the individual swarm units process the tasks in the environment in an efficient manner. This can be achieved using a suitable task selection mechanism that allocates the desired number of swarm units to each task while reducing inter-task latencies and communication overhead, and, ensuring adequate commitment of resources to tasks. In this paper the authors have described and compared different heuristic-based strategies for addressing task-selection in a distributed swarmed system in a multi-agent setting. Experimental results within a simulated environment show that although robots are able to complete the tasks in the system within reasonable time, the performance of the system, especially in the distribution of tasks and robots is sub-optimal [16].

From the above paper I understood a different heuristic-based strategies of task-allocation and execution in a distributed swarmed system in a multi-agent setting.

This paper extends the consensus-based bundle algorithm

(CBBA), a distributed task allocation framework previously developed by the authors, to address complex missions for a team of heterogeneous agents in a dynamic environment. The extended algorithm proposes appropriate handling of time windows of validity for tasks, fuel costs of the vehicles, and heterogeneity in the agent capabilities, while preserving the robust convergence properties of the original algorithm. An architecture to facilitate real-time task replanning in a dynamic environment is also presented, along with methods to handle varying communication constraints and dynamic network topologies. Simulation results and experimental flight tests in an indoor test environment verify the proposed task planning methodology for complex missions [17].

[18]Given the complexity of the cooperative missions considered, there have been numerous solution approaches developed in recent years. This chapter provides an overview of three of the most common planning frameworks: integer programming, Markov decision processes, and game theory. The chapter also considers various architectural decisions that must be addressed when implementing online planning systems for multi-agent teams, providing insights on when centralized, distributed, and decentralized architectures might be good choices for a given application, and how to organize the communication and computation to achieve desired mission performance.

From the above paper I understood different methods of task-allocation and execution on muti-agents for multipurpose missions.

DEMiR-CF is a generic framework designed for a multi-robot team to efficiently allocate tasks among themselves and achieve an overall mission. In the design of DEMiR-CF, the following issues were particularly investigated as the design criteria: efficient and realistic representation of missions, efficient allocation of tasks to cooperatively achieve a global goal, maintenance of the system coherence and consistency by the team members, detection of the contingencies and recover from various failures that may arise during runtime, efficient reallocation of tasks (if necessary) and reorganization of team members (if necessary).Several performance tests are carried out for different domain implementations of the framework. It has been demonstrated that DEMiR-CF is an efficient, scalable, robust and complete framework for a multirobot system [19].

From the above paper I understood a different approach of task-allocation and execution on muti-agents.

In multi-robot systems, task allocation and coordination are two fundamental problems that share high synergy. Although multi-robot architectures typically separate them into distinct layers, relevant improvement may be expected from solutions that are able to concurrently handle them at the same level. This paper proposes a novel framework, called CoMutaR (Coalition formation based on Multi-tasking Robots), which is used for both tackle task distribution among teams of mobile robots, and to guarantee the coordination within the formed teams. Experimental results were performed using the player/stage/gazebo simulator in both loosely-coupled tasks like area surveillance and transportation, and tightly-coupled tasks like box pushing, and the results have shown that our framework was able to successfully resolve the required allocation issues [20]. From the above paper I understood a different approach of task-allocation and execution on muti-agents. I am also using gazebo simulator for conducting experiments for my approach.

III. Spatial Task Allocation and Scheduling in Heterogeneous Teams

In this section, the authors define the concepts that underlie the model of the mission.Then provide a concise statement of the STASP-HMR.

A. *Mission Representation*

Let A be the team of heterogeneous agents available to perform joint mission in an environment of specified dimension. Overall mission is decomposed into a set of tasks $\mathcal{T}$ The tasks can be non atomic,incrementally providing a reward proportional to progress acheived in their completion and can eventually be brought to an en.The spatial layout of tasks is captured by a traversability graph that defines how agents move between tasks [1]. The graph can be represented as G = ($\mathcal{T}$, E) ,where E contains an arc (i,j) if task j can be scheduled right after task i. In general case graph G is complete (i.e. E = $\mathcal{T} \times \mathcal{T}$), and in this we assume all tasks are independent of each other.

From the point of view of the mission, the complete execution of any task $\tau \,\epsilon\, \mathcal{T}$ provides an overall utility, or reward, indicated with R_τ.

B. *Task Efficiency Model*

Task efficiency model as the name suggests is the efficiency with which an agent can perform a specified task. The intution behind this is that any progress on the completion of a task is proportional to overall time devoted to it. In a given time if an agent performs much faster then it is considered more efficient ψ : A $\times$ $\mathcal{T}$ $\rightarrow$ R [1].

IV. Centralized Solution Approach

We formulate the STASP-HMR as stated above by means of a mixed-integer linear program (MIP). An optimal solution to the MIP defines plans for each one of the agents with the goal of maximizing the total mission reward.

$$\max_{\tau \in \mathcal{T}} \quad R_\tau \phi_\tau \tag{1}$$

subject to

$$\sum_{(0,j)\in E} {x_{0j}}^k = 1 \qquad k \in A \tag{2}$$

$$\sum_{(i,0)\in E} {x_{i0}}^k = 1 \qquad k \in A \tag{3}$$

$$\sum_{(i,j)\in E} {x_{ij}}^k = \sum_{(j,i)\in E} {x_{ji}}^k = {y_j}^k \quad k \in A, j \in \mathcal{T} \tag{4}$$

$${t_i}^k + {w_i}^k - {t_j}^k \leq (1 - {x_{ij}}^k)T \quad k \in A, (i,j) \in E, i,j \neq 0 \tag{5}$$

$${y_i}^k \leq {t_i}^k, {w_i}^k \leq T{y_i}^k \qquad k \in A, i \in \mathcal{T} \tag{6}$$

$$\phi_\tau \leq \sum_{k\in A} \psi_k(\tau){w_i}^k \qquad k \in A, \tau \in \mathcal{T} \tag{7}$$

$$0 \leq \phi_\tau \leq C_m(\tau) \qquad \tau \in \mathcal{T} \tag{8}$$

$$\phi_\tau \in \mathbb{R} \tag{9}$$

$${t_i}^k, {w_i}^k \in \mathbb{N} \qquad k \in A, i \in \mathcal{T} \tag{10}$$

$${x_{ij}}^k, {y_i}^k \in \{0,1\} \qquad k \in A, i,j \in \mathcal{T} \tag{11}$$

We use the following decision variables to build the MIP model for the STASP-HMR presented in (1)-(11):

${x_{ij}}^k$: binary, equals 1 if agent k traverses arc (i,j) $\in E$;

${y_i}^k$: binary, equals 1 if agent k is assigned to task i $\in \mathcal{T}$;

ϕ_τ : service provided to task $\tau \in \mathcal{T}$ by all agents;

${t_i}^k$: starting time assigned to task i $\in \mathcal{T}$ by agent k;

${w_i}^k$: time assigned to task i $\in \mathcal{T}$ for agent k.

The objective function (1) defines the quality of a mission plan in terms of its utility, quantifying the expected effect of the agents' activities over the current state of completion map C_m. A dummy vertex denoted by 0 here represents the starting point and ending point of the agents path. Graph G is extended with arcs from 0 to each one of the tasks that are iniatially accesible. Constraints (2-4) ensure path traversability.Contraints 5 eliminate sub-tours together with (6) they define the bounds of the variables t and w. The completion level of each tasks are bounded by constraints (7-8). These bounds ensure that task τtext provides a maximum reward equal to $R_\tau C_m(\tau)$, and that the utility of the plan is contributed with R_τ scaled by the completion of τ (i;e ϕ_τ).Finally, constraints (9-11) set the real,integer, and binary requirements on model variables [1].

V. DECENTRALIZED SOLUTION APPROACH

In decentralized approach each agent runs a replica of the mathematical model, based on local data and limited information sharing.In a decentralized operation, communication among the agents enables the acquisition of relevant information regarding the past, current, and planned activities. This is maintained by a global completion map for all the tasks [1].

VI. Experimental Setup

The aim of the experiment is to survey area using multi-agents.We use heterogeneous robots which includes turtlebots and uavs.We perform the experiment on both centralized and decentralized approaches to compare results.

The experiment is as follows, the total area is divided into multiple cells where each cell is considered as a subtask.we have given reward for each subtask based on the importance of location or cell.If the location is more important to be surveyed by a particular agent then we assigned more reward for that particular agent,for example a subtask with an uneven surface cannot be covered by a turtlebot hence we assign less reward for turtlebots and more reward to uavs for same subtask [2].

The total area to be surveyed by the agent is divided into 30 cells which are represented via 0 to 29 nodes in the traversability graphs.The dummy vertex used is node number 30.The dummy vertex helps to recognize the starting and ending points of the selected traversability path.

The traversability graphs for each agent is same for both centralized and decentralized approach.In Centralized approach the algorithm we solve the algorithm for all agents jointly and assign the best possible sub tasks for each agent.In the decentralized approach we run the replica of algorithm for each agent while considering the information received from other agents. For evaluating the experiment on robots we are using Gazebo simulator and ros.We have created thread for each agent to make them perform tasks simultaneously in the gazebo environment.The linear program tool kit we used for solving the MIP is PULP which is an open source python library.

VII. Results

Figure (1) show the traversability graphs and selected paths for all agents using centralized approach when T = 5 mission intervals. Similarly figure (2) show the traversability graphs and selected paths for all agents using decentralized approach and when look ahead planning T = 5 mission intervals.In the above mentioned figures the traversability graph shown is with out the extension of dummy node. The selcted paths show the dummy node (In our case we have represented it with number 30), the dummy node as mentioned in the MIP model describes the starting and the ending points of the agents selected paths. Figure (3) shows the agents completing assigned tasks simulatenously in the world of gazebo simulator.Figure (4) show the results abtained for Centralized approach.Figure (5) show the results abtained for Decentralized approach.The results show that to complete the same number of tasks Decentralized approach performs slightly slower compared to centralized approach with same number of mission intervals provided information exchange between agents. The link for the source code is https://github.com/niddipi/MILP_to_Collaborative_Missions_with_Heterogeneous_Teams_using_Pulp

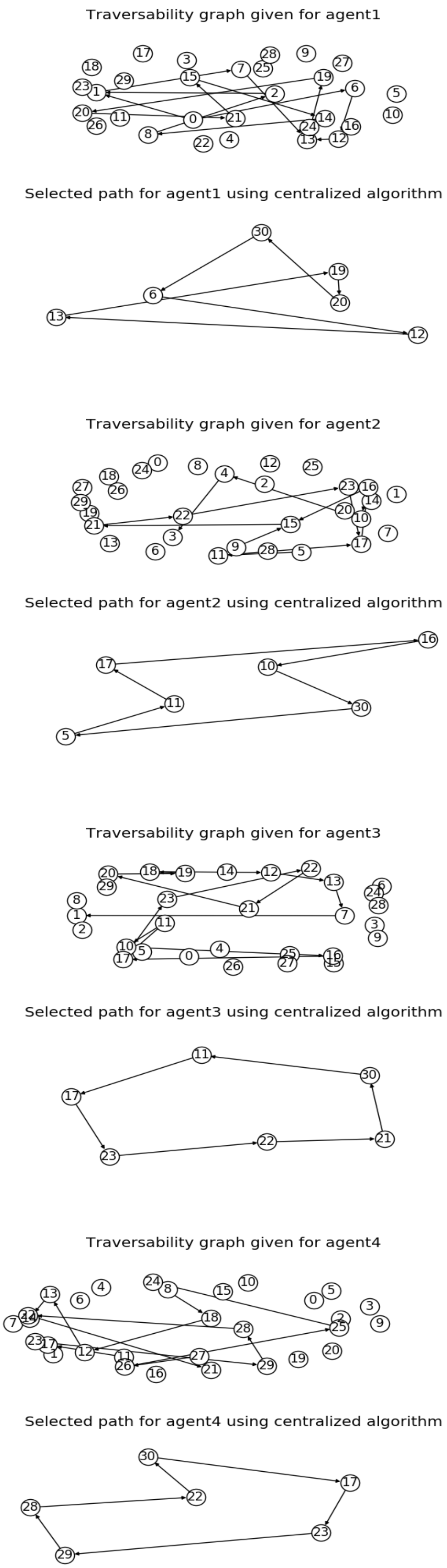

Fig. 1. Results obtained for Centralized approach

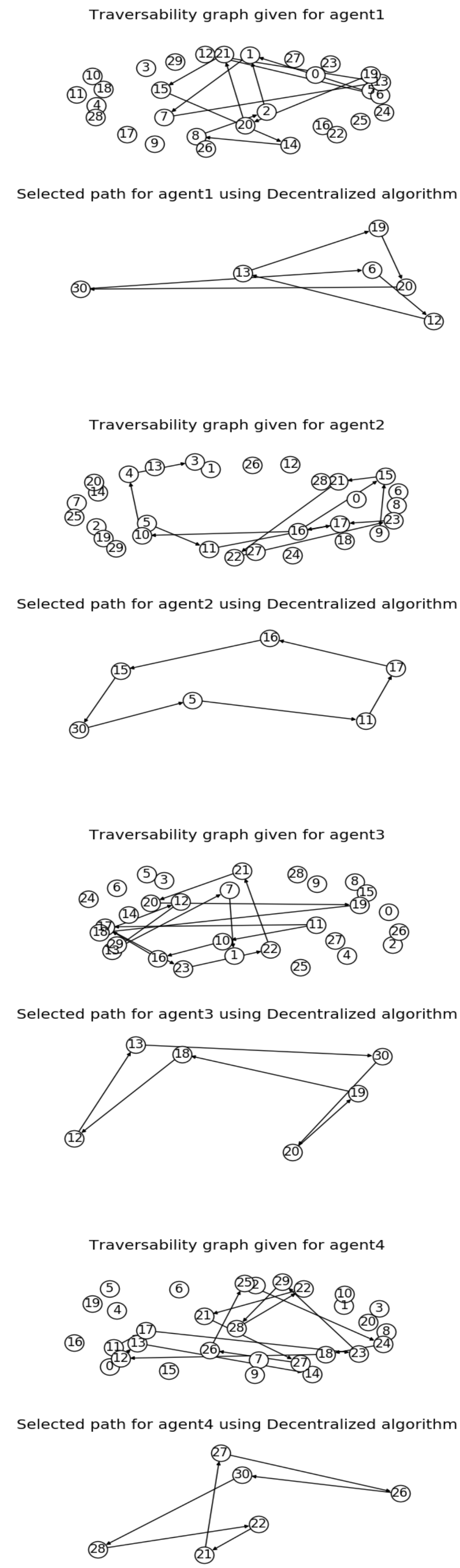

Fig. 2. Results obtained for Decentralized approach

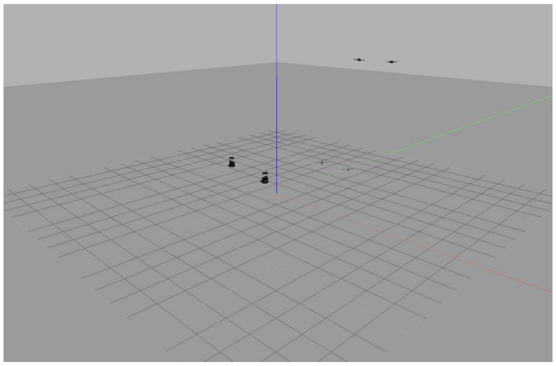

Fig. 3. Heterogeneous robots performing tasks simultaneously

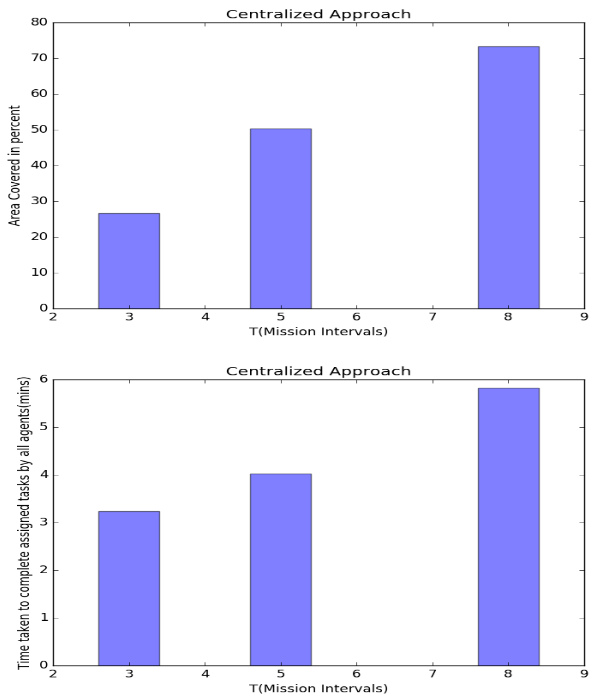

Fig. 4. Results obtained for Centralized approach

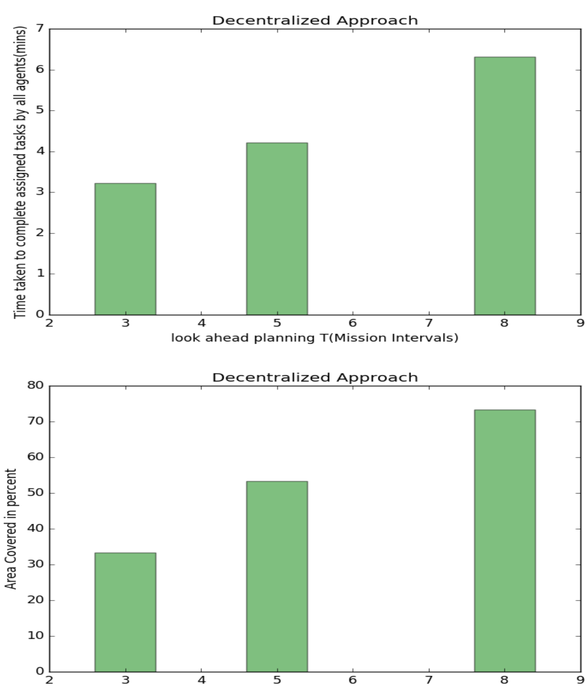

Fig. 5. Results obtained for Decentralized approach

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