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

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***Abstract*—It is crucial to show that a system is adaptable on actual robots along with performing emperical sensitivity analysis and showing that a proposed system works. In our paper we have tested the theoritically proven system on a heterogeneous team of robots in a simulation environment and the results are presented. A mixed integer linear formulation [1] is used to solve the problem of decentralization aiming to find the adaptability on real robots.Our main contributions include comming up with a solution on how to test the algorithm using a heterogeneous team of simulated robots and showing the results centralized and decentralized approaches.**

I. Introduction

Multiple heterogenous team of robots with coordination and planning are answer to many scenarios where human life could be in danger such as serach and rescue scenarios,survelliance etc. Coordination and scheduling is required to avoid conflict, and optimize performance when executing a collaborative mission.In this work we focus on a system which has been proven robust but not tested on any actual robots.For testing the system on real heterogenous team of robots we need peer to peer communication among all robots to share their missions and completion of tasks.But the available on board communication hardware doesnot support peer to peer communication to test on multi heterogenous team of robots. We have tackled this problem using ros platform by creating a ros node for each robot and for peer to peer communication we used rosmsgs .For simulating the heterogenous team of robots we used gazebo which is an open-source well designed simulator for testing algorithms on robots.The problem we considered to test is a Mixed Integer linear formulation to solve the coordination and planning of heterogenous team of robots in a collaborative mission. The algorithm consists of a centralized approach and a topdown decentralized scheme derived from the centralized approach.Our main contribution include comming up with a senario on how to test the algorithm using heterogenous team of simulated robots and showing the results obtained for both centralized and decentralized approaches.

II. Related Work

A variety of work investigates the coordination and scheduling of multi-robot missions other than Mixed Integer problem formulation approach in terms of both centralization and decentralization architectures.Some of them proposed the probabilistic model for a multi-robot grid i;e using Markov Decision Process for spatial task allocation problems [5] [7] [18].Expectation maximization is used for detection of plan deviation for multi-agent cordination in a collaborative mission [5] [3].Heuristic based models are also used for the clustering and opportunistic path planning, to perform a bounded search of possible time-extended schedules and allocations [12] [15] [12]. Some papers has tackled the problem of coordination of multi agents in simulation using Contract-Netprotocol [14] and multiagent-based prototype system that uses swarming techniques [6].some papers provided formal proofs for alogorithms solving multiple agent task assignment to acheive colloborative mission, such as inapproximability results for connectivity constrained multi robot planning with periodic connectivity [11] and consensus-based bundle algorithm (CBBA) [4] [17].Centralized and Decentralized approaches have been proposed and simulation results for their approaches have been shown proving the approaches work, But they have not tested on any simulated or actual robots [1] [2] [8]. Several multi-robot projects are led in different research teams , but up to now few multi-UAVs or multi-Robots(CAR) applications have already been demonstrated [9] [9]. Most of them mainly rely only for unique set of robots such as UAVs or ground robots such as robotic cars. And also most of them use a combination of both wireless networks and cameras to maintian coordination. In our work we focus on use of heterogenous team of robots which consists of both ground (turtlebots) and aerial (quadcopters) robots. The robots which we used are simulated in Gazebo simulator. A few projects have used heterogeneous team of robots for testing their distributed task allocation frameworks [17] [19] [20].But the architectures are different from what we are using(MIP).

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

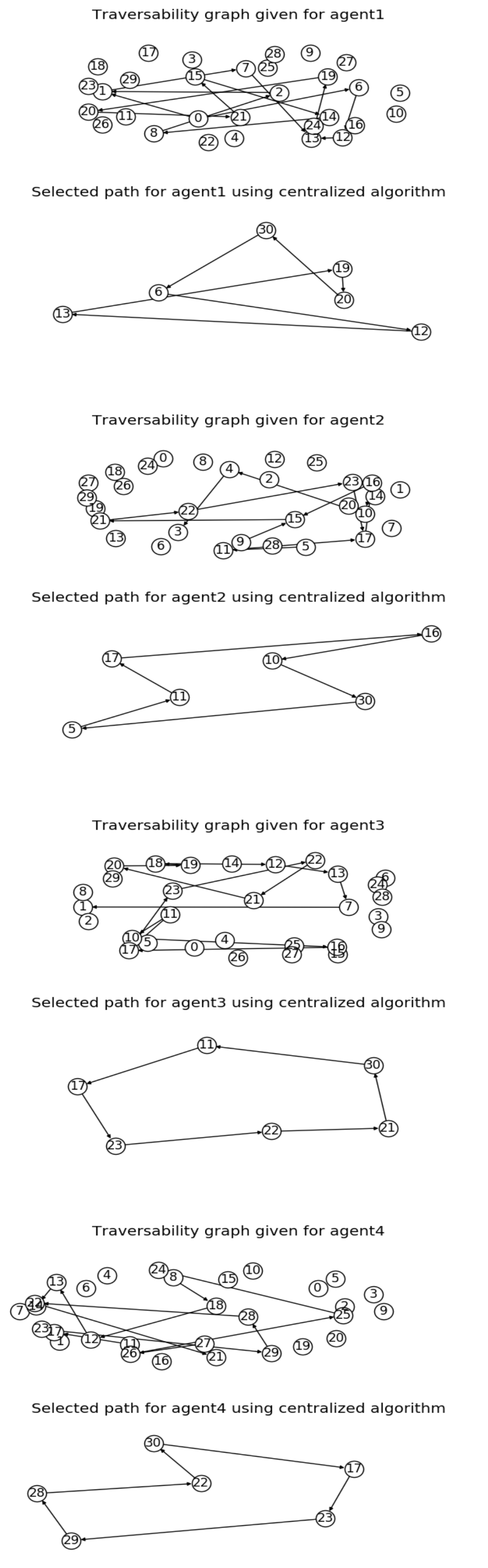

Fig. 1. Results obtained for Centralized approach

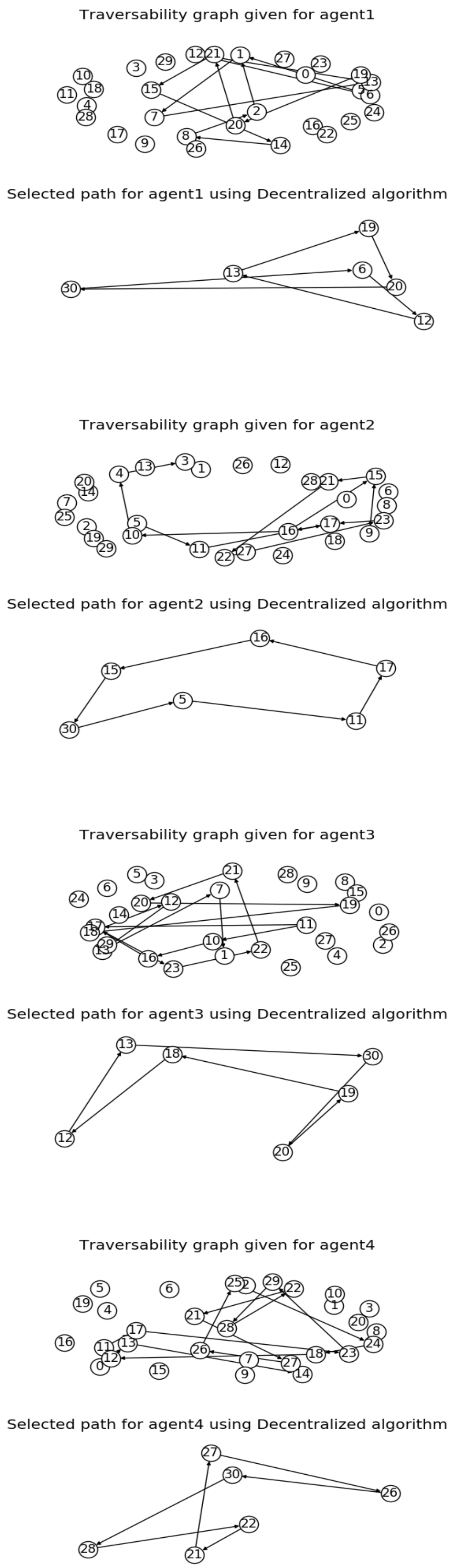

Fig. 2. Results obtained for Decentralized approach

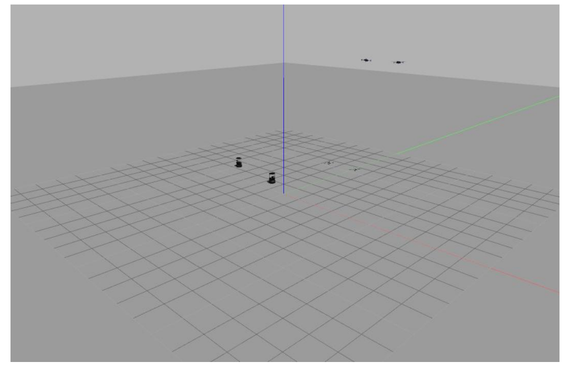

Fig. 3. Heterogeneous robots performing tasks simultaneously

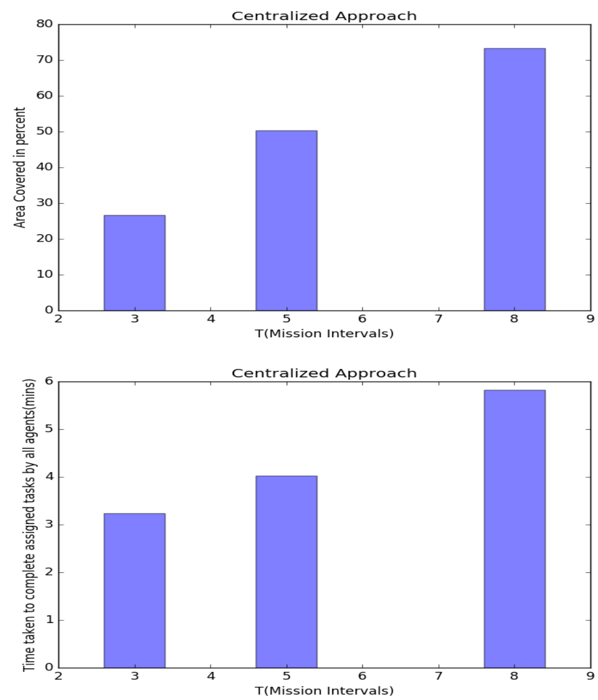

Fig. 4. Results obtained for Centralized approach

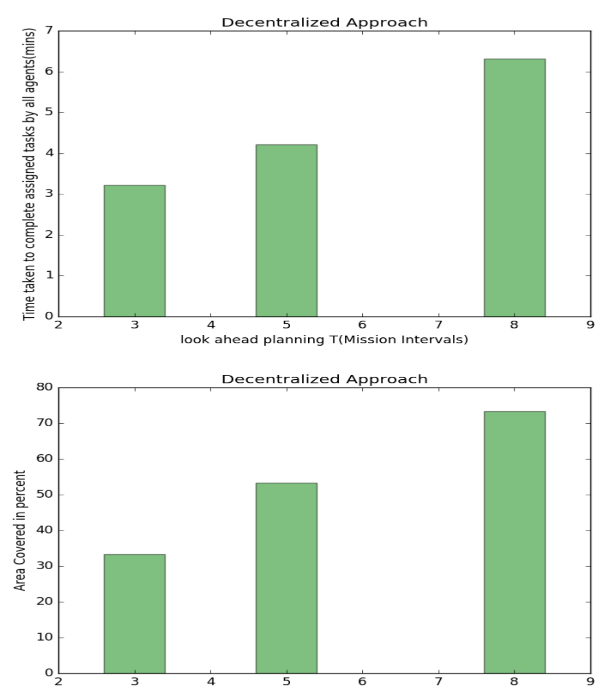

Fig. 5. Results obtained for Decentralized approach

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