An Approach to Supervisory Control of Multi-Robot Teams in Dynamic Domains

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Abstract. This paper explores an approach to human/multi-robot team interaction where a human provides supervisory instruction to a group of robots by assigning tasks and the robot team coordinates to execute the tasks autonomously. A novel, human-centric graph-based model is presented which captures the complexity of task scheduling problems in a dynamic setting and takes into account the spatial distribution of the locations of the tasks and the robots that can complete them. The focus is on problem domains which involve inter-dependent and multi-robot tasks requiring tightly-coupled coordination, occurring in dynamic environments where additional tasks may arrive over time. A user study was conducted to assess the efficacy of this graph-based model. Key factors have been identified, derived from the model, which impact how the human supervisors make task-assignment decisions. The findings presented here illustrate how these key factors capture the complexity of the task-assignment situation and correlate to the mental workload as reported by human supervisors.

Keywords: human-robot interaction, multi-robot coordination, task allocation

1 Introduction

This work investigates possible approaches to improve human performance in *Single-Operator Multi-Robot (SOMR)* control, in domains such as Urban Search and Rescue (USAR), where the human operator interacts with the team at a tactical level, while the lower level control decisions, such as trajectory planning, navigation and collision avoidance, are left to the autonomous platforms. In previous work, different interaction schemes have been developed that include automated planning agents to help a human operator [2]. These studies have shown that these agents may become a hindrance to the human operators *Situational Awareness (SA)* [3] if the proposed automated solutions are not understood by the operators or do not meet the operators' expectations [1].

In this work, we define a formal, graph-based model that captures the complexity of task scheduling problems *from the human operator's perspective.* Our conjecture is that such models are key to improving the interaction between autonomous robot teams and human operators.

The formal model defined here is extended from our earlier model derived for static environments [8]. This extension captures *dynamic* domains, where task allocation occurs simulateously with task execution and new tasks may arrive while allocation—and execution—are underway. Several key parameters are verified via a user study, which is described in Section 3.

2 Methodology

The application domains we consider are complex task environments, where tasks may require multiple robots to work in tight-coordination and/or tasks may depend on other tasks. Our experiment scenarios are inspired from RoboCup Rescue Simulation [6] where heterogeneous groups of agents attend to victims, fires and roadblocks in the aftermath of an earthquake in an urban environment. In our scenarios, a fixed number of robots and tasks are scattered around an office-like environment. The tasks can be either a *sensor-sweep* task, where a robot is expected to go to a specific location and send back sensor information (e.g., camera feed), a *fire-extinguishing* task, resulting from a fire in the environment or a *debris-removal* task, resulting from structural collapses that create debris. These latter two types of tasks may require multiple robots to execute, and they block any access to areas adjacent to those in which they appear. Sensor-sweep tasks can be executed by a single robot and do not block access.

Our problem domain falls into the *Multi-Robot (MR)* and *Instantaneous Assignment (IA)* categories within the taxonomy introduced by Gerkey and Matarić [4] and the *constrained tasks (CT)* and *dynamic allocation (DA)* categories within the extensions added by Landén et al. [7]. The CT dimension signifies the dependencies between tasks, which appear as precedence relationships in our experimental scenarios; for example, a sensor-sweep task that is located inside a room whose entrance is blocked by heavy debris is thus dependent on the completion of a debris-removal task before the sensor-sweep task location can be accessed and the task completed. The DA dimension corresponds to possible changes in the task-assignment problem due to arrival of new tasks while existing tasks are being allocated and/or executed.

We are studying ways in which humans interact with teams of robots faced with the range of *MR-CT-DA* scenarios mentioned above. In earlier work, we developed a graph-based data structure, called a *Task Assignment Graph (TAG)* [8], which represents spatial relationships between task locations and robots. Formally, in an environment containing m robots, $\mathcal{R} = \{r_1, ..., r_m\}$, and n tasks, $\mathcal{K} = \{k_1, ..., k_n\}$, we define $TAG = (V, E)$ as a set of vertices $V = \{v_1, ..., v_n\}$, where each vertex, v_i, represents a task, $k_i \in \mathcal{K}$, and a set of edges E. There exists an edge in E between any two task vertices v_i and v_j *iff* tasks k_i and k_j can be accessed from one to the other in the robots' physical environment. Each task vertex v_i contains a set of robots Acc_i that can access task k_i, and a domain Dom_i which consists of the sets of all possible assignments for that task. The cardinality of each set in Dom_i is defined by the number of robots, Req_i, required to execute task k_i. A vertex may be labelled *critical* if they are responsible for maintaining connectivity between components of the graph (see [8] for details). Essentially, a TAG is a hybrid graph structure that combines a connectivity graph and a constraint network. This level of abstraction allows us to focus on spatial relationships in our analysis, without paying further attention to other specifics of the mission domain or environment.

A TAG models an isolated assignment problem instance. In a dynamic environment, the addition of new tasks will lead to a sequence of TAGs. Here, we introduce a new model, which we call a *Mission Assignment Problem (MAP)*, to reflect the changes to the task-assignment problem space that occurs during a mission. A MAP is an ordered list, $MAP = \langle TAG_0, TAG_1, ...\rangle$, where TAG_i is added to the map at time t_i, and t_0 represents the time when the first task appears. Every entry in the MAP represents a *decision point* for a human who is assigning tasks to robots.

We are studying the impact of the MAP with respect to the human's *mental workload*. We surmise that a few small changes from any TAG_i to TAG_{i+1} will not be difficult to comprehend, whereas many significant changes will quickly overwhelm the human, particularly if these changes occur in rapid succession. Our hypothesis is that mental workload is directly affected by the number of solutions that can be produced for a scenario, which in turn is affected by: *(i.)* the ratio of tasks that require close coordination to the total number of tasks; *(ii.)* the dependencies between the tasks; *(iii.)* the spatial distribution of robot platforms across the environment; and *(iv.)* changes in the environment, such as new tasks that may prevent robots reaching previously assigned tasks.

In our earlier work [8], we identified two factors derived from a TAG which influence the human's mental workload. These are: the *Average Platform Requirement*, $APR = \sum_{i=1}^{n} req_i/n$; and the *Critical Task Ratio*, $CTR = |V_{critical}|/n$. We conducted a user study that involved static environments, and our results verified that both APR and CTR are significant factors with respect to the human's mental demand. In the work presented here, we consider dynamic environments. We identify two new metrics to account for conditions *(iii)* and *(iv)*, respectively. These are: the *Average Domain Density*, $ADD = \sum_{i=1}^{n} DD_i/n$, where $DD_i = |Dom_i|/\binom{req_i}{m}$; and the *Tag Disruption Ratio*, TDR, which is the ratio of the number of assignments removed to the number of assignments performed from one TAG to the next.

3 User Study

We ran a user study in which 30 participants were presented with several RoboCup-Rescue-like scenarios (described above) requiring real-time assignment of tasks to a team of 3 robots. The gender balance of participants was: 10 female (33%) and 20 male (67%). The average age of the participants was 31.5 years, and the average amount of computer experience was 14.9 years.

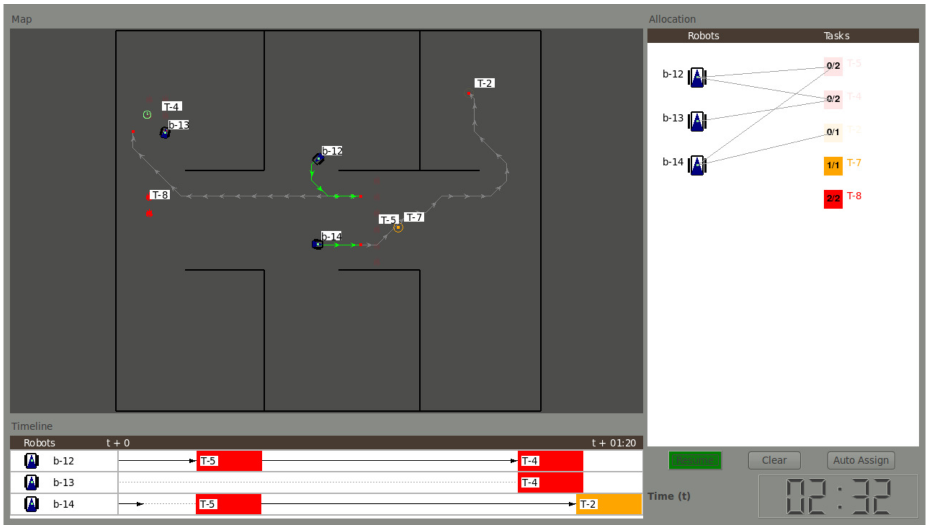

Fig. 1. *TASC Interface. On the left, the map area shows the locations of the robots and tasks. Robots' immediate paths are displayed in green. On the right, the task assignment area is where users allocate robots to tasks. On the bottom, an expected timeline of plan execution is displayed.*

The experiments were conducted with a robot simulation environment and the *Task Assignment Supervision and Control (TASC)* interface (Figure 1). This interface was integrated with the *HRTeam* [9] multi-robot framework, which is built on Player/Stage [5] and was developed in some of our earlier work. In brief, HRTeam facilitates communication between multiple robot controllers, the Stage simulator (or physical robots), and a user interface (e.g., TASC). The TASC interface communicates with the robot controller processes through a set of messages. The robots' locations, paths to their task locations and state information are updated in the interface based on the messages sent by the robots. All task assignments and removals are made via the TASC interface and are immediately updated on the robots. In this setup, the robots operate autonomously with respect to path planning, navigation and collision avoidance. As well, the robots rely fully on the TASC interface to dictate which tasks they will execute and the order in which they will execute them.

Each experiment started with a training session, followed by 4 experimental scenarios. Participants were instructed to distribute tasks to the robots in such a way that the execution of the plan would result in the fastest completion time of all the tasks. In addition, they were instructed to maintain a full assignment of tasks at all times, meaning that they should keep adding tasks to the robots' task queue, without waiting for the robots the complete their immediate tasks. Each experimental scenario contained 8 tasks, two of which were available initially. Every 45 seconds, two new tasks are introduced, one of which was a single-robot task and the other required two robots to complete. To control for order effect and learning effect, the scenarios were presented in randomized order.

Our working hypothesis is that, at the TAG-level, the *Average Domain Density (ADD)*, *Critical Task Ratio (CTR)* and *Tag Disruption Ratio (TDR)* all have an effect on the human's mental workload when assigning tasks to robots. To represent objective mental demand, we measured *Plan Completion Time*, which is the time between the arrival of the new TAG and the time when all available tasks are fully assigned.

4 Results

As above, each participant was exposed to 16 TAGs (4 experimental scenarios, 4 TAGs per scenario—because each scenario's 8 tasks were introduced in pairs). For each TAG, we computed the factors described earlier: TDR, CTR and ADD. We then partitioned the values for each factor into high and low categories (clustered using Expectation-Maximization) and labelled each TAG according to a tuple representing its complexity, $\langle TDR, CTR, ADD \rangle$, e.g., $\langle \mathsf{high}, \mathsf{high}, \mathsf{low} \rangle$. Organised in this way, users were exposed to 0 or more instances of the 8 possible TAG complexities.

We analysed the *Plan Completion Time*, our mental workload metric, for each user, grouped according to TAG complexity. If a user was exposed to a particular TAG complexity more than once, then the average plan completion time was computed for that user. In order to evaluate the impact of each of the three factors on the users' plan completion times, we ran a 3-way repeated measures analysis of variance (ANOVA). The "repetition condition" for each user was considered to be exposure to different TAG complexity levels; thus each user may have experienced up to 8 different conditions[4].

All three factors (TDR, CTR and ADD) were found to have a significant effect on the Plan Completion Time, as shown in Figure 2. For TDR, $F(1, 21) = 12.02$ and $p = 0.0023$; for CTR, $F(1, 25) = 15.59$ and $p = 0.001$; for ADD $F(1, 26) = 8.39$ and $p = 0.0075$. There was no significant interaction found among variables. These intuitive results show clearly that the selected model parameters have significant effect on human subjects' task-assignment time, which was also confirmed during post-experiment inverviews with participants.

5 Summary

In this work, we presented the MAP model for capturing human cognitive workload for dynamic task allocation environment and validated three key factors derived from the MAP, namely: TDR, CTR and ADD. Planned future work includes utilizing the MAP model features and the validated factors for steering an automated decision support agent, in order to improve the interaction between the human operator and the agent.

[4] In reality only 7, because there were no instances of $\langle \mathsf{high}, \mathsf{high}, \mathsf{high} \rangle$ TAGS here.

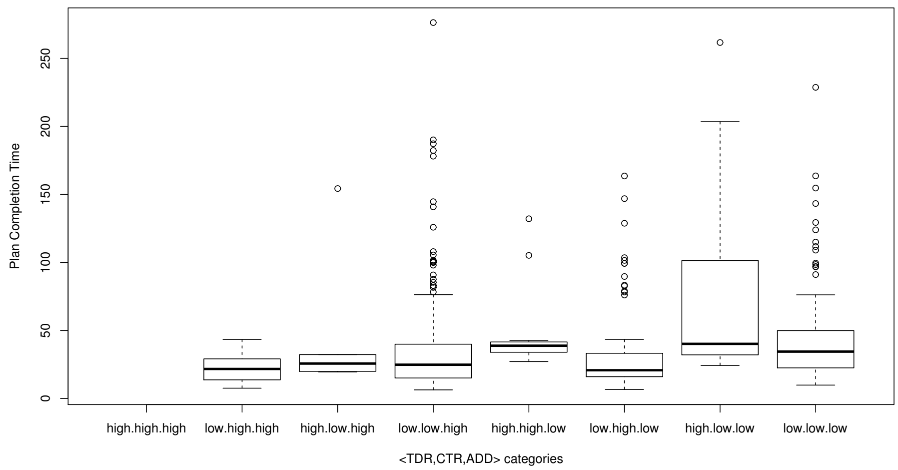

Fig. 2. *Plan Completion Time vs. Scenario categories based on TDR, CTR and ADD*

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