Modeling and Analysis of Task Complexity in Single-Operator Multi-Robot Teams

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ABSTRACT
A model is presented for analyzing the complexity of task assignment in a human/multi-robot team from the perspective of the human team member, or “operator”. The focus is on complex domains where tasks have inter-dependencies and/or require tightly coupled coordination among robots. Preliminary validation of model metrics has been carried out through an experiment involving human subjects. Results suggest significant effect of key aspects of the model on human subjects’ cognitive workload.

Categories and Subject Descriptors
I.2.9 [Robotics]: Miscellaneous; H.1.2 [Models and Principles]: User/Machine Systems—Human factors

Keywords
human multi-robot interaction; supervisory control; complex tasks; metrics; evaluation

1. INTRODUCTION
This paper introduces a model that aims to represent, from the perspective of a human “operator”, task assignment problems in Single Operator Multi-Robot (SOMR) domains. For SOMR settings where higher levels of robot autonomy are practical, tactical supervision is an important factor for increasing the number of robots that human operators can control simultaneously [1]. The model presented here is based on the Single-Robot vs. Multi-Robot (SR,MR) dimension of the robot-centric task taxonomy defined in [2], and the Independent vs. Constrained (IT,CT) dimension defined in [3]. Our contribution is to investigate task/resource allocation problems from the human’s perspective. The results could be used for identifying weaknesses in task assignments, for characterizing behavioral patterns of human operators, and/or for improving the language of interaction between human operators and automated task planning systems.

We restrict our investigation to structured environments where tasks may require tightly coupled coordination among several robots and may have dependencies on one another as a result of constraints imposed by spatial characteristics of the environment. Such constraints may be the direct result of uncompleted tasks blocking access to certain areas, as is the case with the experimental scenarios described in Section 3. Our approach is empirical and introduces a graph-based model that captures key aspects of the problem space. We define evaluation metrics derived from this model and present the results of an experiment with human subjects.

2. MODEL
Our graph-based model, which we refer to as a Task Assignment Graph (TAG), builds on a topological representation of the robots’ environment. A TAG captures spatial relationships between tasks and robots. In an environment containing \( m \) robots, \( R = \{r_1, ..., r_m\} \), and \( n \) tasks, \( T = \{t_1, ..., t_n\} \), we define TAG as \( (V,E) \) as a set of vertices \( V = \{v_1, ..., v_n\} \), where each \( v_i \) represents a task, \( t_i \in T \), and a set of edges \( E \). There exists an edge in \( E \) between any two task vertices \( v_i \) and \( v_j \) iff tasks \( t_i \) and \( t_j \) are accessible from one another in the geographic map. Each task vertex \( v_i \) contains a set of robots, \( Acc_i \), that can access task \( t_i \) 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 \( t_i \). The value of \( Acc_i \) changes dynamically as tasks are completed.

Vertices in a TAG are labeled critical if at least one of the following conditions is satisfied: (i) removing \( v_i \) from the TAG results in multiple disconnected components; (ii) task \( t_i \), together with other tasks, is jointly responsible for robots reaching at least one other task in \( T \); or (iii) task \( t_i \) belongs to a group of tasks which prevent a robot cluster (group of robots co-located in the same part of the map that can access the same set of tasks) from reaching some subset of \( T \). An example of a TAG can be seen in Figure 1(a)-(b).

Based on the TAG, we define two metrics to categorize instances of task assignment situations. To represent the SR-MR dimension of the taxonomy, we define the Average Platform Requirement: \( APR = \sum_{t=1}^{T} req_i / |T| \) where \( |T| \) is the total number of tasks to be assigned. To represent the IT-CT dimension, we define the Critical Task Ratio: \( CTR = |V_{critical}| / |T| \) where \( |V_{critical}| \) is the total number of critical tasks in the scenario.

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3. EXPERIMENT

We conducted an experiment with human subjects to validate the use of APR and CTR as a means to distinguish between task assignment problem instances. Twenty-seven experimental scenarios were defined, with values: \( APR \in \{1.0, 1.5, 1.667\} \) and \( CTR \in \{0.0, 0.333, 0.5\} \). The table below lists the number of experimental scenarios within each of four categories, where low \( APR = 1.0 \), high \( APR > 1.0 \), low \( CTR = 0.0 \), and high \( CTR > 0.0 \):

<table>
<thead>
<tr>
<th>low ( APR )</th>
<th>low ( CTR )</th>
<th>high ( CTR )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>high ( APR )</td>
<td>9</td>
<td></td>
</tr>
</tbody>
</table>

Our hypothesis is that mental demand for human operators aligns with \( < APR,CTR > \) categories.

We ran an experiment to confirm our hypothesis. Fourteen human subjects participated, ranging in age from 19–50 years old and computer experience ranging from 3 to over 15 years. The Task Complexity Assessment Tool (TCAT) [5] was used to present the 27 scenarios to the participants. They were asked to assign a homogeneous team of robots to tasks such that the overall execution time of the tasks would be minimized if the robots executed these tasks. After completing a task assignment for each scenario, participants indicated their perceived mental demand for that assignment, using a format based on the NASA-TLX [4] instrument. The experiment followed within-subject design, where all participants saw the same set of scenarios in randomized order.

For statistical analysis, a two-way repeated measures analysis of variance (ANOVA) test was used with the independent variables \( APR \) (low, high) and \( CTR \) (low, high). The conditions of normality and homogeneity (\( \alpha < 0.05 \)) were met. The effects of both independent variables were found to be statistically significant on mental demand: for \( APR \), \( F(1,13) = 110.8 \) and \( p < 0.001 \); for \( CTR \), \( F(1,13) = 115.8 \) and \( p < 0.001 \). A plot showing mental demand distributions for each scenario category can be seen in Figure 1(c). There is a strong correlation \( r(12) = 0.51, p < 0.001 \) between mental demand and \( APR \), which a surprising result since it was expected that critical tasks would require more mental effort. As indicated during post-experiment interview sessions with human subjects, this effect may be due to participants’ tendencies to reduce the task assignment search space by giving higher priority to critical tasks, which led to fewer alternative solutions to consider for the remaining tasks.

4. SUMMARY

In this work, we introduced the graph-based model, TAG, for representing task assignment complexity in multi-robot settings, based on spatial constraints. This model was assessed through an experiment with human subjects, which suggests that key aspects of the model (\( APR \) and \( CTR \)) have a significant effect on the subjective mental demand metric. Future work includes extending the model to consider the spatial distribution of robots in their environment.

Acknowledgments

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5. REFERENCES


