A Study Assessing the Impact of Task Duration on Performance Metrics for Multi-Robot Teams

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Abstract— **The allocation of tasks to members of a team is a well-studied problem in robotics. Applying market-based mechanisms, particularly auctions, is a popular solution. We focus on evaluating the performance of the team when executing the tasks that have been allocated. The work presented here examines the impact of one such factor, namely task duration. Building on prior work, a new bidding strategy and performance metric are introduced. Experimental results are presented showing that there are statistically significant differences in both time and distance-based performance metrics when tasks have zero vs greater-than-zero duration.**

I. INTRODUCTION

Assigning a set of tasks within a team of robots is known as the *multi-robot task allocation (MRTA)* problem. As the number of tasks and size of the robot team increases, the number of possible allocations rises at an exponential rate. The complexity further increases when factors are added, such as a dynamic environment that changes over time, a heterogeneous team of robots with various capabilities or tasks that have prerequisites which must be satisfied before they can be executed. Finding the optimal solution to an MRTA problem is known to be NP-hard [1], [2], so a popular family of strategies takes a *market-* or *auction-*based approach. Auctions are useful because they can distribute workload amongst team members whilst reflecting preferences of individuals [2], [3], [4]. A local optimum is determined by each robot (labelled *bidder*) and these optima are collectively reconciled by an *auctioneer*. The team can operate in real-time and respond dynamically to changes in the task landscape, such as the arrival of new tasks to be addressed while already executing tasks previously allocated.

The work presented here extends our prior work in which we demonstrated the importance of mission execution and weighing various performance metrics when comparing task allocation mechanisms [5], [4]. Here we assess the impact of *task duration*. Our contributions include: (a) a new methodology for robots to bid on tasks with varying durations; (b) a new metric that attempts to capture aspects of task duration; (c) results of experiments conducted both in simulation and on physical robots across a landscape of mission parameters; and (d) statistical analysis of results to highlight the impact on performance metrics when task duration varies.

This work was conducted while the first author was a masters student in the Dept of Informatics at King's College London, UK. The second author was a professor in the same department and project supervisor.

II. BACKGROUND

Koenig et al. [2] proposed *sequential single-item (SSI)* auctions in which several tasks are announced to team members at once; each robot responds with a bid representing a cost to the robot for executing the task, e.g. the distance the robot must travel to reach the task location. An auctioneer identifies the winner as the robot with the smallest bid. The auction repeats in *rounds* until all tasks have been allocated. SSI combines the strength of *combinatorial* [6] (bidding on bundles of tasks) and *parallel single-item (PSI)* [2] (allocating all tasks in a single round) auctions. SSI has been a popular choice for MRTA and several variants have been studied, for example tasks with temporal constraints [3], tasks with precedence constraints [7], [8], and tasks with pickup-and-delivery constraints [9]. Our prior work has focused on empirical analysis of auction mechanisms [5], comparing SSI, PSI and a baseline *Round Robin (RR)* (first come, first served) in experiments conducted on physical and simulated robots. We have defined a comprehensive set of performance metrics [10] and learned a model for selecting an appropriate mechanism given mission parameters [11].

III. APPROACH

We assess the impact of varying task durations on multi-robot team performance by executing missions on physical robots and in simulation, and then analysing differences in performance metrics. Missions are defined across a landscape of parameters [1], [12] which distinguish characteristics of tasks, robots and the environment: *single robot (SR)* vs *multi-robot (MR)*—SR tasks can be completed by one robot, whereas MR tasks require the cooperation of multiple robots; *independent (IT)* vs *constrained (CT)*—IT tasks can be executed in any order, whereas CT tasks are dependent on others due to factors such as precedence order; *static (SA)* vs *dynamic (DA)*—SA tasks are known before a mission starts and can be allocated before any execution, whereas DA tasks arrive dynamically and are allocated during execution of other tasks.

Here, we introduce a *task duration* parameter, i.e. the time it takes to execute a task: *instantaneous (ID)* vs *extended (XD)*—ID tasks take no time to execute (i.e., 0 seconds), whereas XD task length is > 0. We compare four XD variants: *XDC*, where all tasks have the same constant length; *XDG*, where task length is chosen randomly from

(a) TurtleBot3 Burger (b) arena

Fig. 1. Experimental setup.

a Gaussian distribution; *XDP*, where task length is chosen randomly from a Poisson distribution; and *XDR*, where task length is chosen randomly from a uniform distribution[1].

We also introduce a new bidding strategy that calculates the estimated time for a robot to travel to a task location instead of using travel distance as the basis of a bid. Thus the bid takes into account the estimated travel time as well as predicted task duration. The bid value b of robot r for a new task x is calculated as: $b_r = \sum_{i=1}^{N_r}(T_{i-1,i} + E_i) + T_{N_r,x}$, where N_r is the number of uncompleted tasks robot r is assigned, T is the estimated time to travel between two task locations[2] and E is the predicted duration of task i.

IV. EXPERIMENTS

We conducted a series of experiments with physical and simulated Turtlebot3 robots (Figure 1a) using the *MRTeAm* [5], [10] framework built with Robot Operating System (ROS). Our experimental arena emulates an office-like area divided into rooms and corridors (Figure 1b).

For our experiments, we employed three different *auction mechanisms* (*RR, PSI, SSI*) two different *starting configurations*: *clustered* together in one portion of the arena or *distributed* around the arena; two different task constraints (*IT, CT*); and five task durations (*ID, XDC, XDG, XDP, XDR*). For each combination of parameters, at least 5 runs were conducted in the physical environment and 15 runs in simulation. In total, 1926 runs were completed.

Three performance metrics are analysed to assess the impact of task duration: the total *distance travelled* collectively by all the members of the robot team; the total *run time* from the start of a mission until all tasks are completed; and *service delay time*, the time from when an auctioneer awards a task until a robot begins executing the task. Service time is a new metric introduced here to reflect the time each task "waits" before a robot arrives at its location. Service time measures how quickly a task's execution can commence or how long the task was delayed, i.e. left unattended. Arriving at a task location quickly is an important factor in many application domains, especially in emergency situations. A shorter service time is preferred because it means the robot team is able to arrive at task locations more promptly.

[1]The values employed here are: XDC: length=15 seconds; XDG: $\mu = 15$ and $\sigma = 3$; XDP: $\lambda = 15$; XDR: range=$(5, 35)$.

[2]T is calculated as the predicted travel distance times the average robot velocity, which was determined experimentally to be $0.12m/s$.

V. RESULTS

Our analysis assesses the impact of task duration on the three performance metrics. For brevity here, we present aggregated results and make three comparisons: (a) across all five task duration values; (b) instant versus extended time; and (c) across the four extended time values. The number of runs per aggregate are: *ID*: $N = 330$, *XDC*: $N = 508$, *XDG*: $N = 469$, *XDP*: $N = 379$, and *XDR*: $N = 240$.

We looked for statistically significant results. After checking that the data within each sample is normally distributed[3], we tested for differences using *analysis of variance (ANOVA)*, with $p < 0.01$ as the threshold for statistical significance. The results of statistical testing on individual variables are shown in Figure 2, which illustrates the distributions for each sample and indicates, for each of the three types of analysis (above), which differences amongst samples are statistically significant.

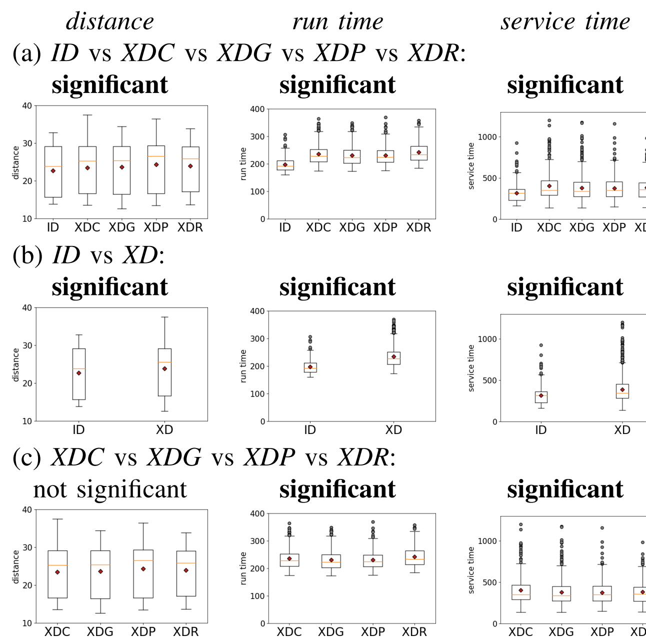

Fig. 2. Statistical differences. Statistical significance is noted where ANOVA produces $p < 0.01$.

VI. SUMMARY

We have presented a study assessing the impact of task duration on three different performance metrics collected from experiments with multi-robot teams. We have introduced a new bidding strategy which accounts for task duration and a new metric for measuring performance delay due to task duration. Statistical analysis of our results shows that there are significant differences in all performance metrics when tasks have non-zero duration (*ID* vs *XD**) and in time-related metrics when duration varies randomly according to probability distributions defined by similar parameter values.

[3]Using the Shapiro-Wilk test [13]

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