Master Thesis Defense Ángela Patricia Enríquez Gómez

Date: Monday, 20.07.2020
Time: 13:00
Room: Online

Title: Multi-Robot Task Allocation with Temporal Constraints and Uncertain Durations

Abstract:
Multi-robot systems work together to achieve a common goal, e.g., to execute a set of tasks. Multi-Robot Task Allocation (MRTA) algorithms assign tasks to robots based on an optimization criterion, such as the total completion time. In addition, tasks can have temporal constraints that limit the time at which robots start executing tasks. The ROPOD project develops multi-robot systems to perform transportation tasks within hospital facilities. Tasks are received on-demand and must be executed within user-defined times, e.g., a supply cart must be collected between 9:00 and 9:05 from a room and delivered to a different room within the same building.

The Temporal Sequential Single-Item auction (TeSSI) algorithm allocates tasks with temporal constraints, producing compact schedules in polynomial time, thereby scaling the number of robots and tasks well. However, this algorithm relies on task duration information and does not consider that task durations can only be estimated, but not known beforehand. Variations in robot velocities and unexpected obstacles, such as overcrowded hallways, affect these durations. TeSSI uses Simple Temporal Networks (STNs) to represent task schedules, but other temporal networks, such as Simple Temporal Networks with Uncertainty (STNU) and Probabilistic Simple Temporal Networks (PSTNs) extend STNs to deal with uncertain durations. There is a lack of MRTA approaches that consider uncertainty during the allocation process, and to the best of our knowledge, neither STNUs nor PSTNs have been used for task allocation.

This work extends TeSSI to use STNUs and PSTNs in combination with state of the art temporal solvers (SREA, DREA, and DSC), resulting in three new MRTA approaches: TeSSI-SREA, TeSSI-DREA and TeSSI-DSC. Moreover, it presents three delay recovery methods (preemption, re-allocation, relaxation of constraints) to react to delays at execution time, and components for an MRS architecture to allocate, schedule, and monitor robot schedules. Uncertainty is modeled in terms of Probability Density Functions (PDFs). The estimated time to travel between locations on the map is expressed as a normal distribution, and this information is obtained from historical data.

The proposed approaches are compared with TeSSI. The resiliency of the allocations is tested by introducing minor and significant variations in task durations at execution time. The effect of recovery methods on the number of tasks executed on-time when tasks have tight, loose, and random temporal separations is evaluated. Furthermore, the impact of the fleet size in the distribution of tasks among robots, as well as the effect of an increasing number of tasks and robots in the allocation times is analyzed.

The experimental results show that all three new methods outperform TeSSI, both when the model of uncertainty reflects the durations encountered at execution, as well as when the model underestimates task durations. TeSSI-DREA achieves a success rate of 0.98 for tasks with tight temporal separations and non-intentional delays, while TeSSI obtains a completion rate of 0.79 for the same case. TeSSI improves its performance when combined with the re-allocation recovery method, but its success rates remain lower than those for the other approaches. TeSSI-SREA and TeSSI-DREA have, in general, the best success rates, with no significant difference between them. Since TeSSI-SREA requires fewer computations than TeSSI-DREA and achieves a high level of success with a minimal use of recovery methods, it is considered to be the most suitable approach for allocating on-demand transportation tasks.