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An Evolutionary Algorithm Based Framework for Task Allocation in Multi-Robot Teams

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Abstract

Multi-Robot Task Allocation (MRTA) has no formal framework which could provide solutions covering different domains within the MRTA taxonomy without changing the optimization scheme. This research aims to develop a novel framework using evolutionary computing. The study proposes a modular approach towards developing this framework in which individual problem types of the MRTA taxonomy are solved one at a time. The performance of the framework will be evaluated against the popular approaches suggested for each problem type.

Introduction

Efficient planning is one of the main skills required to accomplish a complex task by a team of agents. Multi-Robot Task Allocation (MRTA) is the problem of determining the optimal assignment of a group of tasks to a team of robots for efficient completion of the job at hand. With increasing affordability of mobile robots and human reliance on them, the need for effective task allocation has increased.

The first and the most fundamental question, in this case, is; which agent performs what task? To answer this question, some optimization strategy needs to be executed. The strategy should keep all the spatial, temporal, and physical constraints of the team in check while providing an optimal plan. This research intends to use evolutionary algorithms (EA) for this purpose. The reason for using EA is that they have proved to be more flexible in real-life dynamic environments compared to other optimization techniques.

MRTA was classified by (Gerkey and Mataric, 2004) on a widely accepted 3 axes taxonomy. The taxonomy distinguishes among (a) Robot Type: Single task robots (ST) vs Multiple task robots (MT), (b) Task type: Single robot tasks (SR) vs Multi-robot tasks (MR), and (c) Task Arrival (in time): Instantaneous arrival (IA) vs Time extended (TE).

Problem Statement

Most of the work done towards solving MRTA has addressed either one or at most two isolated problem scenarios. For real life scenarios, however, an intelligent agent should be able to switch between different situations without having the optimization architecture changed. The current literature has no effective framework which can take a team of robots through multiple cases of the MRTA taxonomy. Thus, there is a need for a framework which could work across multiple scenarios while keeping the team more autonomous, efficient and effective.

Methodology

The first stage of the framework deals with the simplest problem of the MRTA taxonomy, that is, ST-SR-IA. A simple optimization scenario for a team of robots is solved using EA. The task is provided in the form of the x and y coordinates of the jobs where a robot has to reach. The fitness is judged on the basis of the total distance traveled for job execution by the team.

Figure 1(a) gives the chromosome representation for a 12 job, 3 robot, ST-SR-IA problem. The chromosome has a two part representation; the first part determines the order of job execution while the second part assigns jobs from part 1 to each robot. Considering the example of Figure 1(a), jobs 1, 9, 12, 3, and 4 are to be done by robot1, jobs 7, 8, 5, and 11 are to be attempted by robot 2 and jobs 2, 6, and 10 are to be accomplished by robot 3. Crossover and mutation operators are designed in alignment with the representation scheme so that all the possible combinations present in the solution space are explored.

The next stage of the research aims to solve ST-MR-IA type problems. The stage 1 representation is not changed in order to make the proposed framework generic. Figure 1(b) provides a potential solution for an 8 MR-task, 3 robot, ST-MR-IA problem. For this particular representation, robot 1 is responsible for one part of task 3, that is, 3.2 (task 3 is an MR task having 3 instances, namely 3.0, 3.1, and 3.2) and task 1.0. Robot 2 takes care of 2.1, 3.1, 4.0, 5.1, 6.0, 7.0, and 8.0 while robot 3 handles tasks 3.0, 2.0, and 5.0.

To better understand the relatively complex MT-MR-IA problem, let us consider a team of robots which has to recover an injured soldier from the battlefield. One of the robots might be given a secondary task of relaying the body vitals of the soldier to the base station while recovering him. Although the team has the primary task of recovering the injured, one of the robots will be given this additional secondary responsibility. Hence, a secondary task (monitoring the vitals) will be merged with a primary task (recovering the body) to make a robot perform multiple tasks. The MT-MR-IA representation will be similar to the one used for ST-MR-IA in which secondary tasks are clustered with existing primary tasks using a clustering algorithm. A similar scheme is suggested by (Jones, Dias, and Stentz, 2011). The proposed approach will have all secondary tasks clustered with primary tasks as additional constraints; constraints which are to be met by any robot attempting that particular primary job. The rest of the implementation will be very similar to ST-MR-IA

The last phase of this research would focus on Time Extended (TE) version of the mentioned tasks. This phase would convert the already implemented ST-SR-IA, ST-MR-IA, and MT-MR-IA to their time-extended versions. The aim here is to make the proposed framework iterative so that it could provide optimal solutions without complete knowledge of the environment. In addition, and more importantly, the EA should be able to restart from partially optimal solutions as new tasks are explored in time.

1.0	9.0	12.0	3.0	4.0	7.0	8.0	5.0	11.0	2.0	6.0	10.0	5	4	3

(a) ST-SR-IA Chromosome representation for 12 jobs and 3 robots

3.2	1.0	2.1	3.1	4.0	5.1	6.0	7.0	8.0	3.0	2.0	5.0	2	7	3

(b) ST-MR-IA Chromosome representation for 8 Multi-robot jobs and 3 robots

Figure 1: Chromosome representation

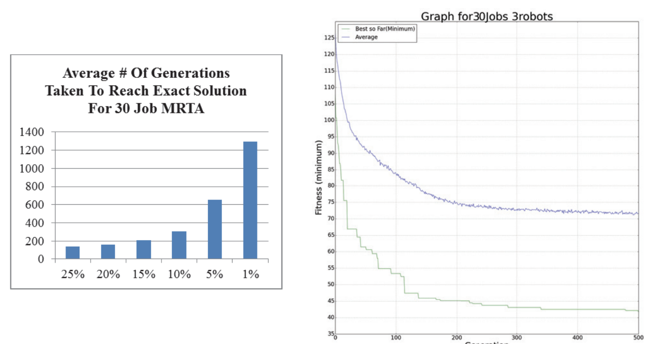
Experiments and Results

Experiment I related to ST-SR-IA has been completed. The experiments involved a team of 3 homogeneous robots and 10 to 30 tasks. For validation, a Multi-traveling Salesman (MTSP) based representation was modeled in AMPL and solved for the same job distributions. The solutions (distance traveled) for both EA and MTSP were exactly the same for all the task distributions; proving that our EA was reaching the exact solution every time. Figure 2(a) shows the average generations taken by the EA to reach certain percentages of the optimum solution while Figure 2(b) demonstrates the ASF (average-so-far) and BSF (best-so-far) curves for a 30 job problem. Since a fixed number of randomly generated solutions are injected in every generation, the ASF and BSF curves never meet (Figure 2(b)).

Experiment II related to ST-MR-IA is in its final stages of implementation. The representation shown in Figure 1(b) is used by the EA. A centralized auction based scheme is implemented for validation purposes. The auction based scheme has been widely researched and used in MRTA community (Martinson and Arkin, 2003).

Experiments III will be covering MT-MR-IA type problems. There are only a handful of publications that have already worked on this type of problems, and any one of those techniques would be used for the validation purpose.

Experiment IV onwards will focus on making the schemes, developed till experiment III, iterative by solving ST-SR-TE, ST-MR-TE, and MT-MR-TE types of problems. The test cases developed in previous 3 experiments will be used in a timed-task-arrival manner for validation purposes. The results are expected to be comparable with their Instantaneous Arrival based variants.



(a) *(b)*

Figure 2: 30 Job, 3 Robot, EA results (ST-SR-IA)

References

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