Task Allocation for Rescue Robotics:
A Replicator Dynamics Approach

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Abstract
Task allocation on homogeneous rescue robots has been an important research field in recent years due to the advance in both robotics and artificial intelligence. Nevertheless, catastrophic scenarios still represent a complex challenge because of the complexity and uncertainty of their characteristics and parameters which produce highly heterogeneous tasks as a result of the different nature of problems they are intended for. We hereby propose an approach to the catastrophic condition uncovered above by solving the replicator dynamics equation to reduce the effects of uncertainty. A standard metric based on task progress is defined and the main elements of game theory like payoff matrix and allocation ratios are computed in order to obtain the number of robots assigned to each task. Finally, software was built for simulation; by using this software some scenarios were defined and simulations were run to compare and validate our approach.

1 Introduction

The use of robots in catastrophic scenarios is one of the main research fields in robotics, due to both the need to support people after a disaster and scientific and technical opportunities therein. Previous works on rescue robotics have been developed from specific disciplinary approaches; however, after a catastrophic event it is necessary to perform several tasks such as mapping, navigation, structural health inspection (SHI), life support, etc. All these tasks are heterogeneous as a result of the objectives they aim for, the operations they perform and the methodology established for their metrics. Game theory is a meta-heuristic method commonly used for negotiation and tasks allocation in multi - agent systems providing optimal solutions for a wide range of disciplines. Nevertheless, there are two great challenges when facing rescue tasks allocation with game theory: the intrinsic uncertainty in the tasks (objectives, resources, size, etc.) and the definition of an appropriate payoff function to compute with.

2 Normalization of Heterogeneous Tasks in Rescue Robotics

Table 1: Summary of rescue tasks for robotics [1], their objective and the main metric proposed in this work.

Task	Objective	Main Metrics
Search	Search victims	Number of found victims
Mapping	Map of the disaster zone	Covered area
Rubble removal	Clean and secure	Clean area
Structural inspection	Determine safe structures	Number of structures
In situ medical assessment	First aid assistance	Number of supported victims
Extraction and evacuation	Telemedicine	Number of transported victims
Mobile repeater	Enlarge communications coverage	Coverage area
Serving as a surrogate	Support human tasks	Number of functions
Adaptively shoring	Secure structures	Number of structures
Providing logistics support	Automation in the supply chain	Number of provisions

We point out that a set of methods for each rescue task can be selected for carrying this out.

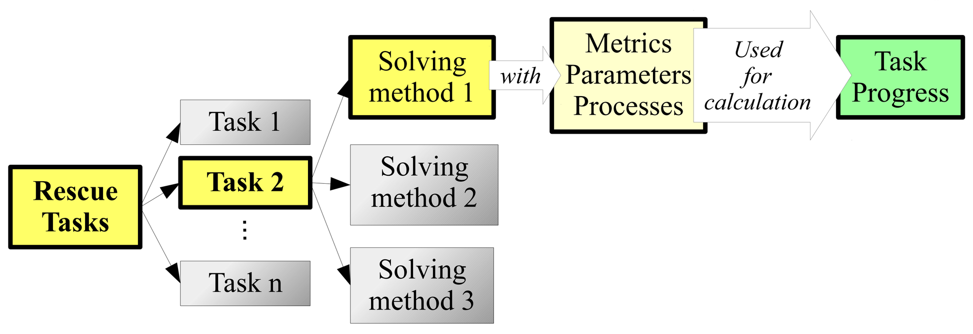

Figure 1: Perspective of rescue tasks and their characteristics used in this work for task progress calculation [2], [3]

3 Game Theory for Task Allocation [4], [5]

- $m \in \mathbb{R}^+$: population of agents or players.
- $\mathcal{S}$: finite set of available pure strategies, $\mathcal{S} = \{1, .., n\}$
- $\mathbf{p} = [p_1, ..., p_n]$: state of the population, where p_i indicates the mass portion of players choosing the strategy $i \in S$.
- Simplex:

$$\Delta = \left\{ \mathbf{p} \in \mathbb{R}^n_{\geq 0} : \sum_{i \in \mathcal{S}} p_i = m \right\} \quad (1)$$

- $\mathbf{f} : \Delta \to \mathbb{R}^n$: payment vector, where $\mathbf{f}(\mathbf{p}) = [f_1(\mathbf{p}), ..., f_n(\mathbf{p})]$.
- Average fitness:

$$\bar{f}(p) = \frac{\sum_{i \in \mathcal{S}} p_i f_i(\mathbf{p})}{m} \quad (2)$$

- Main dynamics:

$$\dot{p}_{\mathrm{i}} = \sum_{j \in \mathcal{S}} p_{\mathrm{j}} \rho_{\mathrm{ji}} - p_{\mathrm{i}} \sum_{i \in \mathcal{S}} \rho_{\mathrm{ij}} \quad (3)$$

- Replicator dynamic:

$$\dot{p}_{\mathrm{i}} = p_{\mathrm{i}} \left(f_{\mathrm{i}}(p) - \bar{f}(p) \right) \quad (4)$$

3.1 Proposal of metrics to evaluate progress

1. Advance percentage

$$a_i(\%) = \frac{N_i * T_s}{w_i} * 100 \quad (5)$$

a_i: Advance for task i, N_i: Number of agents dedicated to task i, T_s: Sample time and w_i: Total robot hour of the task

2. Task progress percentage

$$TP_i(\%) = TP_i + a_i(\%) \quad (6)$$

3. Pending task

$$PT_i(\%) = 1 - TP_i(\%) \quad (7)$$

We have proposed as payoff function to 9, a the diagonal matrix constructed with elements by computing equation (8), PM. For each task there is an exact set of robots assigned to execute it; it is possible for that to be an empty set.

$$pm_i = \frac{\frac{\prod_{j=1}^{n} w_j}{w_i}}{\sum_{k=1}^{n} \frac{\prod_{j=1}^{n} w_j}{w_k}} * PT_i \quad (8)$$

$$\mathbf{f}(\mathbf{p}) = PM * \mathbf{p} \quad (9)$$

4 Simulations and Results

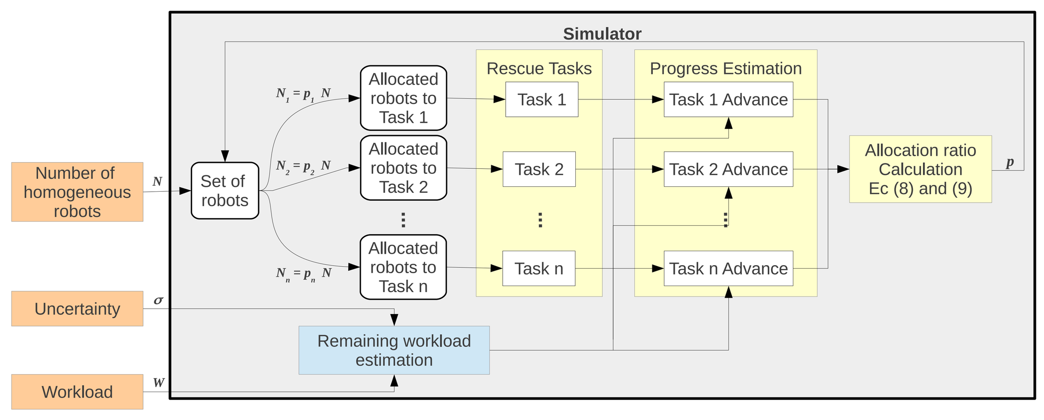

Figure 2: Overall structure of the built simulator software.

All scenarios are simulated with a sample time (T_s) of 1 hour, an integer number of robots and allocated robots. A quantity of 100 homogeneous robots is set to be divided in the three tasks.

Table 2: Parameters used for simulation (* only used for scenario 2).

Task	W (in robot hours)	W[50] (in robot hours)*	v(t)*	p[0]
0	800	1000	N($\mu = 0, \sigma = 1$)	0,7
1	5300	500	N($\mu = 0, \sigma = 1$)	0,1
2	2400	4000	N($\mu = 0, \sigma = 1$)	0,2

4.1 Scenario 1: ideal conditions

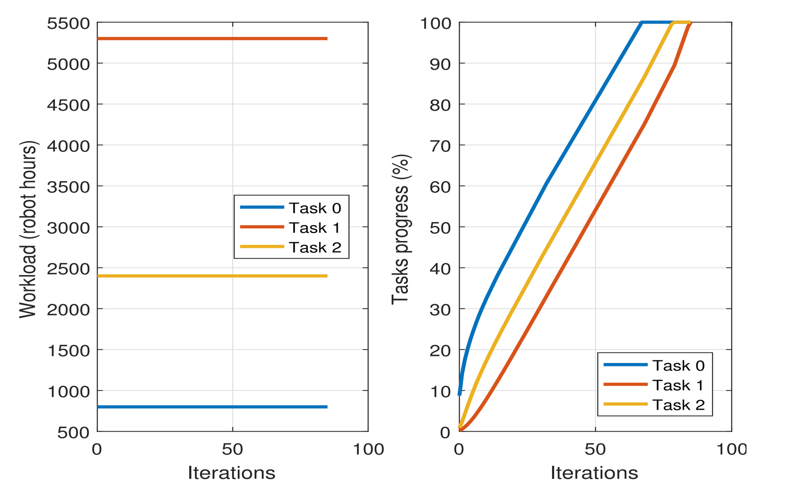

Figure 3: Workload as income (left) and task progress as outcome (right).

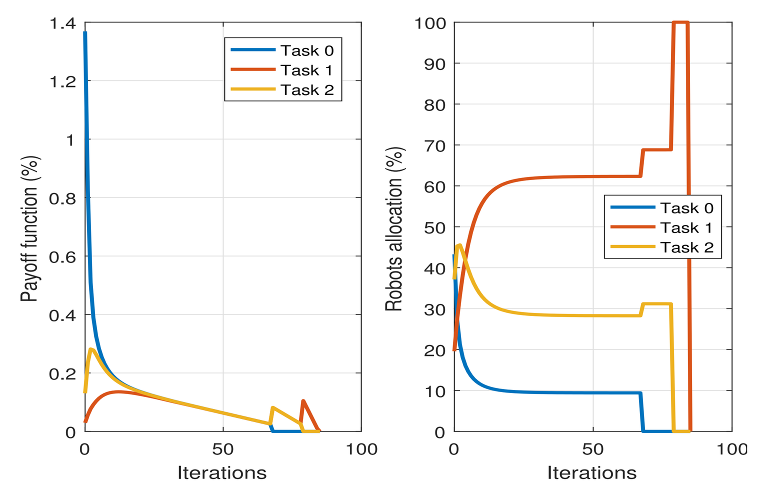

Figure 4: Payoff computed for each task based on (left) and the obtained robot allocation percentage per tasks (right).

4.2 Scenario 2: Change on Workload and Stochastic

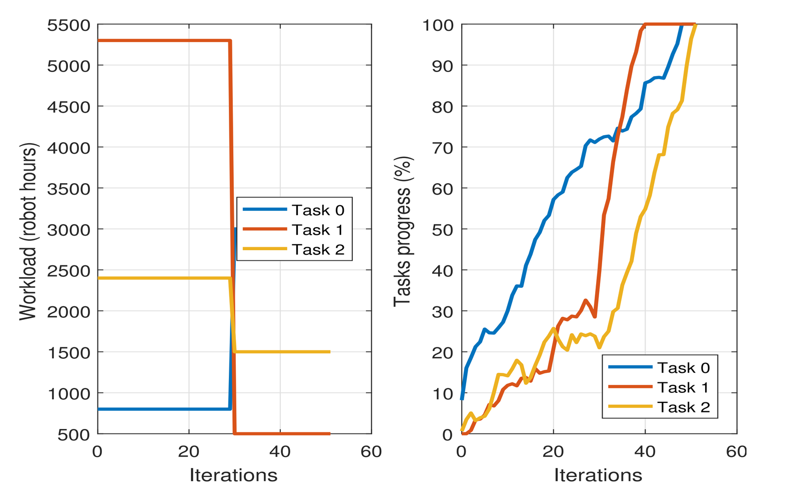

Figure 5: Workload with change due to new information of tasks on iteration 50 (left) and task progress with stochastic behavior (right).

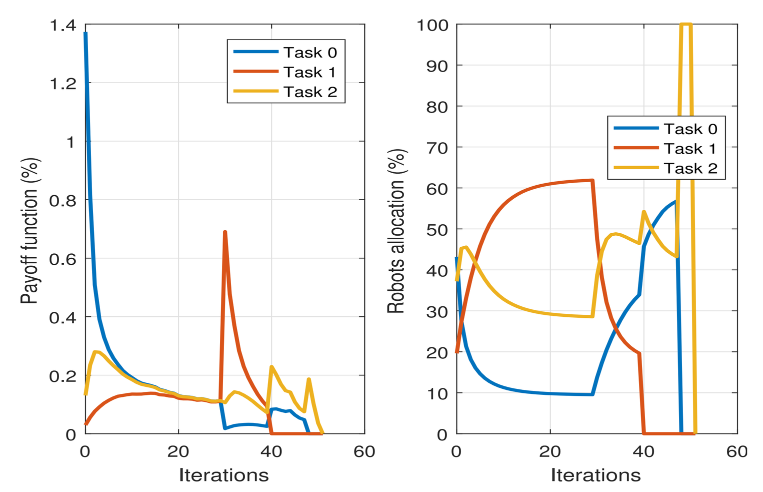

Figure 6: Payoff computed for each task based on (left) and the obtained robot allocation percentage per tasks (right).

5 Conclusions

- The use of advance and progress in task execution was proposed here as a common metric for tasks and the definition of workloads (necessary robot time to finish a task) as cost for every task. Other possible definitions can be done as well in future works adding uncertainty and new information availability.
- We have proposed a linear behavior for task progresses but real ones can be defined in other ways as exponential behaviors. Another topic to improve the method here proposed is the inclusion of task - changing costs to represent the lost in time and energy produced when a robot is re-allocated for a different task.
- We have taken advantage of the replicator dynamics equation to find the optimal allocation of homogeneous robots into sets of heterogeneous rescue tasks; we also obtained a reduction in the impact of uncertainty in the allocation.
- It is the objective of an additional work to test and propose other payoff definitions for non linear scenarios which are closer to real ones.
- A formal convergence and stability study is encouraged after the results of the work.

References

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