Market-Driven Multi-Agent Collaboration for Extinguishing Fires in the RoboCup Rescue Simulation Domain

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Abstract

Market-driven methods are the applications of basic free market economy principles to multi-agent planning tasks. They take advantage of the communication among the team members for maximizing the overall utility of a team of agents, one example of which is the rescue agents competing in the RoboCup Rescue Simulation League. In this paper, a modified market-driven algorithm and its integration to the behavioral architecture implemented for fire brigade agents of the rescue team are described. The algorithm is shown to provide a remarkable increase in the overall profit of the team.

1. Introduction

RoboCup Rescue Simulation (RSL) is one of the competitions in RoboCup (RoboCup-Rescue, 2008). Impacts of an earthquake such as collapsed buildings with civilians buried under them causing roads to close, and fires caused by gas leakages constitute the main theme of the competition (Morimoto, 2002). In order to minimize the damage associated with the disaster, rescue agents with different specializations and various responsibilities are employed. Ambulance teams are responsible for saving civilians under collapsed buildings, fire brigades are responsible for extinguishing fires, and police forces are responsible for clearing road blockades. The RSL team of Boğaziçi University, RoboAKUT, is a multi-agent rescue team developed for this competition and has been competing since 2002, and won the first place in the RSL Agent Competition in 2010. This paper presents the improvement achieved in multi-agent planning by using an integrated application of Market-Driven Methods (MDM) and Behavior-Based (BB) approach.

2. Approaches to Search and Rescue Mission

There are several approaches to solve the optimum utility problem in the RSL domain. In one extreme, there are the "every man for himself" kind of algorithms that are only based on individual utilities and costs in planning. In the other extreme, there are algorithms aimed at optimizing the overall utility through consideration of the overall utility of the team. BB approach is a good example for the former kind and MDM is a classic case for the latter.

2.1 Behavioral Method

BB architectures stem from the need due to the lack of performance and robustness of deliberative architectures which are simply sense-plan-act loops. They depend on principles of decomposing intelligence, distributing planning over acting, and taking advantage of emergent behaviors; henceforth achieving a reactive and robust planning. Disjoint behaviors form the basis of this method. Arbitration mechanisms, such as subsumption, are used to regulate the precedence of behaviors (Brooks, 1991). RSL domain consists of tasks of varying complexity for agents specialized in performing those tasks. Decomposition method used in construction of the BB model for RoboAkut 2010 is as shown in Figure 1 (Yılmaz & Sevim, 2010).

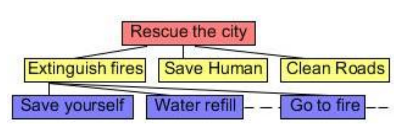


Figure 1. Pure behavioral method.

2.2 Market-Driven Method

MDM aims at maximizing the overall gain of a group of robots by cooperation, collaboration, and/or competition between them. This cannot be achieved merely by maximizing the profits of all individuals in a group; rather, it is necessary to take the total profit of that group into consideration while planning. The key to "deciding for all" is the communication between the robots for trading jobs, power, and information. Distributed or centralized decision mechanisms may be used depending on the structures of teams (Kose et al., 2005).

3. Proposed Application of MDM

The proposed improvement on the former system is the integration of the MDM and BB methods to the system. This will be achieved as shown in Figure 2. As can be observed, an extra behavior, compared to the pure behavioral approach in Figure 1, that applies the market logic is added to the system. For every task, this market implementation will be specialized in order to meet the specific needs of that task.

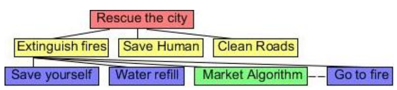


Figure 2. Market-driven method included into the current behavioral one.

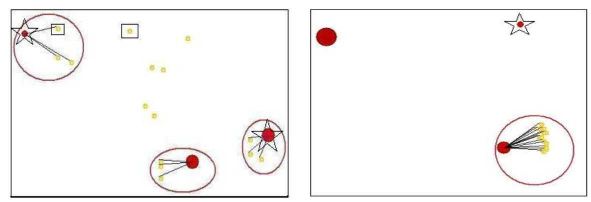
In the implemented market algorithm, every agent without an assignment calculates the costs for its known fires, and sends the best two of these costs to the center. The center, using its auction tools adds those bids to the appropriate auctions and gathers results for the auctions. If according to the results one agent is assigned to more than one building, an auction weighing the priority of the building and the cost for agent in taking action against that building is held on those results and the final decision is sent to the agent. If according to the results one agent is not assigned to any building, it is added in the auctions held for three buildings with the highest priority and no utilization, and the results involving more than one agent are interpreted using the method described above. During the cycles of central decision, an agent starts its action for the building with the least cost to it and according to the final decision by the center, it either preempts its current action or not. We believe that this algorithm is one of the best alternatives for RoboAKUT as it does not put much strain on the current communication structure and it is easily applicable to the current infrastructure.

4. Tests and Results

For testing the effectiveness of MDM in the RSL domain, scenarios associated with fires around a city have been extracted and used in the construction of a standalone system simulating only fires (some snaphots are given in Figure 3). During the tests a simple BB algorithm is compared with the variations of MDM algorithms.

4.1 Test Environment

For testing purposes a separate simulator working on a simple task, which we call "Extinguishing Fires Around a City", is developed and used (Figure 3). This task is chosen because it is simple to work on, hence can improve the productivity; yet even in a city with a small number of buildings and fire brigade agents there are many possible scenarios which enhance our testing abilities. It also provides a great environment as some of the factors that seriously affect the whole process but also those ones that are hard to observe in a complex structure become obvious in it. An example to these is the clustering tendency of agents, which can be explained as the physical grouping of agents around fires due to lack of communication between them. In MDM, the agents do not group as in Figure 3(a). However, this is an important problem in a simple BB implementation where the agents hardly know about each other. Grouped agents probably miss some other fires, as can be seen in Figure 3(b).



(a) MDM Screenshot (b) BB Screenshot

Figure 3. Screenshots of the test tool (Spots in squares: Agents, Filled Circles in Star:Fires, Strokes:Assignments, Big Hollow Circles:"Clustering effect")

4.2 Test Cases

In the testing phase the aim is to observe whether there is any difference between a system using a pure BB architecture and a system using some combination of MDM and BB approaches. Another objective is to observe the improvement in MDM algorithms as the parameters of the cost function are varied to find the optimal solution.

We tested various versions of the market-driven algorithms combined with behavioral structure against a purely behavioral one. Across the versions, there are both algorithm and parameter variations. There are some major versions that determine the main algorithmics and some minor versions that investigate the changes in market-driven method's results across different size of clusters where a cluster size represents the maximum number of agents allowed to engage in a particular fire event.

- $Version_1$ is the purely behavioral one hence it is used as the control group.
- $Version_2$ is the implementation of the algorithm

explained under the Application of Market-Driven Method section. $Version_{2-sv1}$, $Version_{2-sv2}$, $Version_{2-sv3}$, $Version_{2-sv4}$ and $Version_{2-sv5}$ are the variations of $Version_2$ where the cluster size is limited to one, two, three, five, and eight, respectively. This way we get to observe the effect of the size of a group on the overall performance.

- $Version_3$ is a variation of $Version_2$ in which the agents wait until the decision of the center. $Version_{3-sv1}$, $Version_{3-sv2}$, $Version_{3-sv3}$, $Version_{3-sv4}$, and $Version_{3-sv5}$ are the variations of $Version_3$ where, as in the case for $Version_2$, the cluster size is limited to one, two, three, five, and eight, respectively.

Along with $Version_2$ and $Version_3$ there are two other versions, namely $Version_{2-m}$ and $Version_{3-m}$. In these versions due to some changes in the associated parameters, a standard fire brigade's extinguishing capacity is decreased. The same versioning applied to $Version_2$ and $Version_3$ is applied to these versions as well. Every test is tried on 100 different scenarios. Those results are interpreted statistically using their averages and standard deviations.

4.3 Results

For interpreting Table 1 and Figure 4, we should consider the explanations provided in the former section. In Table 1 concatenating the row headings with column headings we can obtain associated results in the intersections of those rows and columns.

Table 1. Test results: "Average scores gained"

Ver.	*sv.1*	*sv.2*	*sv.3*	*sv.4*	*sv.5*	*Inactive*	
1						-36.62	
2	72.05	59.35	37.43	8.07	-8.33		
2-m	22.75	33.95	21.00	0.34	-15.00		
3	72.35	55.81	33.59	5.72	-11.40		
3-m	23.71	31.01	18.11	2.03	-17.50		

In all 100 scenarios we applied our tests on, there were, on average, 89 fires. The scores in the table represent the difference between the fires that were extinguished and those that were not. Observing the results in Figure 4 and Table 1 we see that there is a significant difference between $Version_1$ and all others. This is to an extent due to the low scores of the behavioral planner; partly because it is not a robust, and a fully developed planner yet, but this does not pose a problem since the market algorithm is integrated just on this planner and all that differs in the results are due to the market approach. Apart from that, a very important reason for the significant difference is the fact that in $Version_1$ all the agents go to the same fire due to the "grouping tendency" explained in Section 4.1. Since

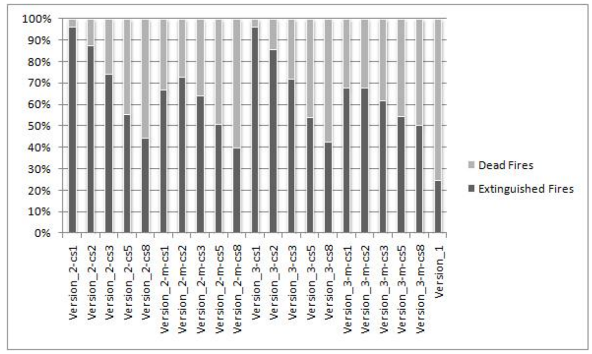
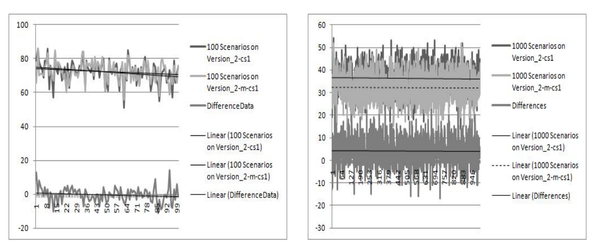


Figure 4. Results, Proportion of Extinguished Fires (darker) to Dead Fires (lighter) and All the Fires can be observed

the agents group around earlier fires, they cannot manage other fires easily. In the implementations of the market-driven approach, since all the agents are in contact with a center, they are directed by the center to wherever they are needed. This way, physically close agents form a team directed by the center and since they are distributed better on the map they get better results.

Between $Version_2$ and $Version_3$, the effect of an extra degree of reactivity (starting an action without waiting the center's permission) provided to the agents is tested. For interpretation, the average of the differences between the corresponding scenarios is used. The results seem to be too close when only 100 scenarios are considered (Figure 5(a)). However the more reactive approach proves to be useful when 1000 scenarios are considered as the difference becomes significantly larger than 0 (Figure 5(b)) supporting the superiority of the relatively more reactive approach over the relatively less reactive one. For example, in an experiment run on 1000 separate scenarios for $Version_{2-sv3}$ and $Version_{3-sv3}$ it is observed that the average of differences of scores is 4.022 (Figure 5(b)) although it is 0.3 (Figure 5(a)) in a test involving only 100 scenarios.



(a) For 100 scenarios, Avg. of Differences is 0.3 (lower trendline)

(b) For 1000 scenarios, Avg. of Differences is 4.022 (lower trendline)

Figure 5. Difference between all the results of $Version_{2-sv3}$ and $Version_{3-sv3}$. Average of differences can be observed with the help of trendlines

$Version_{2-m}$ and $Version_{3-m}$ are included to emphasize the results of different versions. These cases are obtained by decreasing the capacities of the agents by half. As can be seen although the results for $Version_2$ and $Version_3$ imply that as the cluster size (mentioned in the section for the test cases) becomes smaller the scores tend to increase, the results for $Version_{2-m}$ and $Version_{3-m}$ show us that there is no such pattern since the results for clusters of size one are not better than the results for clusters of size two. This result points to a relation between the chunk size and the capacity of agents and it should be utilized in the cost function.

5. Conclusion

As can be seen in the test results, the market algorithm is a very important factor in enhancing the scores through communication between the agents which leads to cooperation and collaboration. Collaboration improves scores by avoiding "excessive clustering" around disaster events and provides a close-to-optimum distribution of work, man, and power resources around jobs in an intelligent manner, taking into consideration the important factors like collective capacities of a groups versus jobs.

Due to the complex nature of the search and rescue task there are many additional parameters that need to be considered which will be covered in future work.

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