Task allocation in rescue operations using combinatorial auctions

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Abstract. The simulation scenario of RoboCup Rescue is a dynamic and changeable environment, where rescue agents have to mitigate a disaster. Rescue agents tend to carry out the activities nearest to them. This leads to increasing entropy in the organization of rescue activities, with various rescue agents getting involved in the same task. Such a situation is obviously undesirable. This paper provides an approach for distributing rescue agents in a more rational way, by using combinatorial auction techniques to perform task allocation. The RoboCup Rescue platform has been used as the framework for the problem.

Introduction

A disaster environment is a dynamic environment with unpredictable situations. The kinds of rescue activities that take place depend on the kind of disaster that has occurred and can range from rescuing victims, to extinguishing forest fires, re-establishing urban services, cleaning beaches, etc. Rescue resources should be assigned in such a way as to accomplish the various tasks required for optimal recovery from the disaster. Technology should be able to make a contribution in this socially significant situation and to this end, several initiatives have been developed in order to promote research in such complex scenarios. Two examples are Pacifica [3] and RoboCup Rescue [5], both of which provide standard problems in which technologies can be examined and integrated. Such artificial scenarios are restricted to specific domains making the problem easier to tackle. In this study, we worked with RoboCup Rescue.

One of the RoboCup Rescue scenarios is the simulation league where several heterogeneous rescue agents interact with one common purpose: to mitigate the damage caused by an earthquake in a populated city. In such conditions, fire brigades, police forces, and ambulance teams have to be coordinated to rescue victims, extinguish fires and unblock roads. The key issue in this environment is to assign rescue agents to perform these tasks according to the agents' capabilities with the ultimate goal of maximizing the number of rescued victims.

Task allocation is difficult because of the different sources of environmental dynamics. First of all, agents are submitted to continuous danger, so rescue agents can also be injured or even killed. Second, the effects of the disaster are continuous: fires spread if they are not extinguished; burning or weakened buildings may collapse and block roads, etc. And third, the rescue task itself is not known beforehand: civilians in need of rescue are discovered through exploration by the rescue agents.

Most approaches follow a task allocation method based on criteria of distance: each agent performs the task located nearest to them. This leads to increasing entropy in the organization of rescue activities, with various rescue agents getting involved in the same task. This situation is obviously undesirable. In addition to locality, other criteria should be taken into account for task allocation, such as, for example, the presence of other agents acting in the vicinity. There are several techniques for dealing with multiple criteria decision making [4], but, bearing in mind the dynamism of the problem at hand, we think that combinatorial auctions are a good choice for tackling the problem [1,7,9]. In this paper we present such an approach.

This paper is organized as follows: Firstly, the rescue scenario is introduced in section 1. Then, in section 2, we present the concepts of *combinatorial auctions* and the *winner determination algorithm*. In section 3, we describe the application of the algorithm to the RoboCup Rescue domain and in section 4, we illustrate the entire process with an example. Finally, we provide some conclusions and discussions.

1. Rescue scenario

The rescue scenario provided by RoboCup-Rescue [2] is a disaster environment caused by an earthquake (see Figure 1). In this scenario, there are collapsed buildings, fires, and blocked highways, people in a state of panic looking for safe ground, and rescue agents helping victims. Fire brigade agents, police forces and ambulance teams comprise the rescue agents, in addition to central agents made up of the fire, police and ambulance stations. In the current version of the RoboCup Rescue Simulation League, there are initially 72 civilian agents, 5 ambulance team agents, 10 brigade agents, 10 police force agents, 1 ambulance station agent, 1 fire station agent and 1 police station agent in the disaster area. All the agents have the same objective - to minimize the damage and rescue victims within the earthquake scenario.

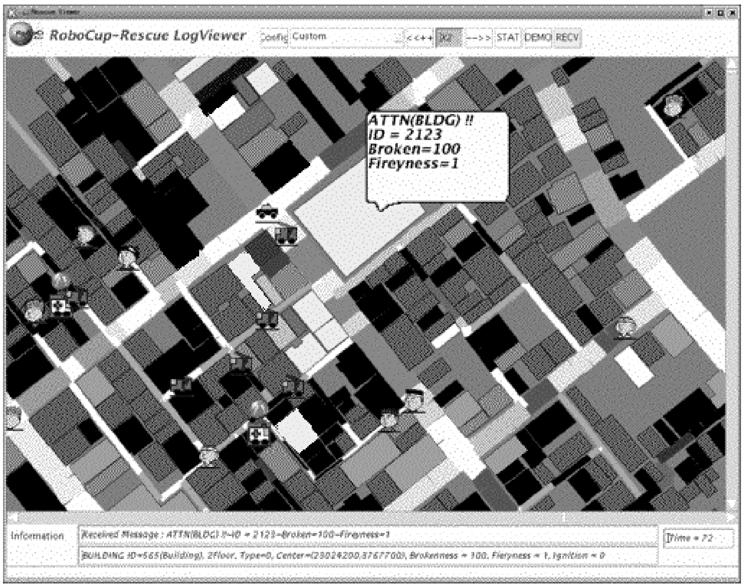

Fig. 1. Rescue scenario.
Central buildings, rescue agents, houses, civilians, blocked roads (grey) and fires (from yellow to dark-red). The fire brigade agents are represented in the simulator viewer by a fire truck, the police agents are represented by a police car, the ambulance team agents are represented by an ambulance, and the civilians are represented by images of people.

1.1 Types of agents

In the simulation environment, there are two main types of agents: rescue agents and victims (civilians). When the earthquake happens, some civilians can move to nearby refuges to find safety. However, most of them either die or are buried and injured. The survival possibilities of the latter depend on the activity of the rescue agents.

The rescue agents are classified into moving and fixed agents (see Figure 2). The moving rescue agents are the fire brigades, police force and ambulance teams. The fixed agents are the central agents, i.e. those who cannot move, such as the fire, police and ambulance stations.

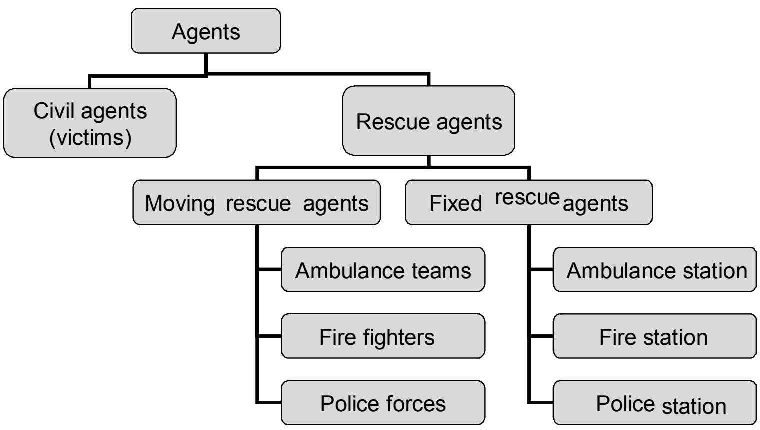

Fig. 2. Types of agents in the RoboCup-Rescue scenario.

1.2 Agents properties

All agents have certain general properties, namely *id*, *hp*, *damage*, *position* and *buriedness*. *Id* is the identification code of the agent. *Hp* measures the remaining life of the agents. *Damage* shows whether or not the agent has been injured. *Position* indicates the location where the agent is in the rescue scenario. Finally, *buriedness* indicates whether the agent can move or is buried under a pile of objects. Other specific properties depend on the type of agent. For example, fire brigade agents have properties such as *water quantity*, which shows how much water is in the tank, and *stretched length* which shows how far their hose can be unreeled [6].

1.3 Agents capabilities

Every type of agent has certain perception, action and communication capabilities, as shown in Table 1. First, *perception capabilities* relate to the limited range of perception that agents have in real situations. Moving agents can see visual information within a radius of 10 meters. Visual information is in terms of collapsed buildings, victim location and so on. Fixed agents cannot perceive visual information.

Secondly, the activities each agent can carry out are constrained by *action capabilities*. Ambulance teams are able to rescue civilians (*load, rescue, unload*). Fire fighters can extinguish fires (*extinguish*) and police forces can clear roads (*clear*) so that other agents can move.

Type	Capabilities
Civilians	Sense, Hear, Move, Say
Ambulance team	Sense, Hear, Move, Say, Tell, Rescue, Load, Unload
Fire brigade	Sense, Hear, Move, Say, Tell, Extinguish
Police force	Sense, Hear, Move, Say, Tell, Clear
Central agents	Hear, Say, Tell

Table 1. Agents' capabilities

Finally, *communication capabilities* constrain the communication among the different types of agents. Agents can exchange messages by voice (*say* and *listen*) and communication services (*tell* and *hear*). In the former, other agents located within a 10-meter radius can perceive the message. In the latter case, the message is perceived by the same type of agents located in a 30-meter radius. Central agents can communicate with other central agents using communication devices (*tell* and *hear*).

An agent is capable of saying or listening to, a maximum of 4 messages in each simulation cycle, within which a decision to perform some action should be taken. This is a tough constraint imposed by the Robocup Rescue simulator which should be taken into account when implementing an appropriate communication strategy (See for example [12].

2. Combinatorial auctions

In an auction, the seller wants to sell certain items and get the highest possible payments for them, while each bidder wants to acquire the items at the lowest possible price. In a sequential auction, the items are auctioned one at a time [1]. In a combinatorial auction, there is one seller (or several sellers acting in concert) and multiple bidders which may place bids on combinations of items [7]. The final objective is to obtain the maximum benefit for the seller by determining the appropriate set of winning bids (i.e., the winners).

There are several approaches for dealing with combinatorial auctions from which we have selected a particular search algorithm for its simplicity and complexity properties (see [9] for a complete analysis of these).

2.1 Winner determination problem

In an auction, it is the auctioneer who determines the winners. A non-combinatorial auction is solved by picking the highest bidder for each item separately, but in a combinatorial auction, deciding who the winner is much harder.

Let's say M is the set of items to be auctioned. Then, an agent *i*, can place a bid, $b_i(S)>0$, for any combination $S \subseteq M$.

Let's say $\bar{b}(S)$ is the highest bid price for a combination. If several agents submit the same combination of items, the bid with the highest price is the only one kept, and the others can be discarded as irrelevant (they are less beneficial for the seller). Then, the highest bid price for a combination is:

$$\bar{b}(S) = \max_{i \in bidders} b_i(S) \quad (1)$$

Let W be a partition on the set M so that each item is included in, at most, one of the subsets. Then, $S \in W$. And let A be the set of all possible partitions, that is, $W \in A$.

The goal of the winner determination method is then to find a solution that maximizes the auctioneer's revenue given that each winning bidder pays the prices of her winning bids:

$$\max_{W \in A} \sum_{S \in W} \bar{b}(S) \quad (2)$$

2.2 The search algorithm

According to [9], the optimal winner determination problem can be solved by using a search algorithm. The search space is defined as follows: nodes keep information on bids and paths provide combinations of bids.

The list of bids is denoted by $\{B_1, ..., B_n\}$. Each bid B_j is a tuple $<S_j, \bar{b}_j>$ composed by the set S_j of items in the bid and the price $\bar{b}_j$ of the bid.

Each path is a sequence of disjoints bids, so that no items are shared. That is, for any path $pk=\{B_{k1}, B_{k2,} ... B_{km}\}$, it holds that $S_{k1} \cap S_{k2} \cap ... \cap S_{km} = \varnothing$. A solution is a path in which

$$S_{k1} \cup S_{k2} \cup ... \cup S_{km} \leq M.$$

In order to generate a solution, nodes are generated in lexicographic order of the set of items of the bids. For example, given the following bids:

B_1=<(319, 1230),10>
B_2=<(2500,3829),21>

bid B1 will be selected first, since the first item on the bid combination of B1 is 319, and the first item of B2 is 2500, i.e., 319 < 2500.

The cost g_k of the path p_k is defined as:

$$g_k = \sum_j \bar{b}_{kj} \quad (3)$$

Obviously, the paths that interest the auctioneer are the ones that lead to a maximum g value.

The heuristics of the search algorithm is defined as h = g + f, where g is the cost of the path up to the current node, according to (3), and f is the cost of the bid to be selected, that is, $\bar{b}_i$

3. Application to rescue operations.

In this approach each central agent (fire station, ambulance centre and office police) are the auctioneers and each rescue team (fire brigade, ambulance team and police force) are the bidders. The bid items are the tasks and the final objective is to obtain the maximum benefit for the whole system.

At the beginning there are no rescue operations to be performed, since the agents are just exploring the situation in their surrounding area. In order to start the combinatorial auction, the stations need to gather information from the rescue agents in terms of victims, fires and blocked roads.

3.1 Gathering tasks

Ambulance centres decide upon victim operations, fire stations upon fire extinguishing operations and police forces upon road unblocking operations. When an ambulance team discovers a fire, it cannot send this information to the fire station directly (see the description on communication capabilities in the previous section), so a communication strategy is required.

Our communication strategy emphasizes the role of the moving agents in gathering information about tasks for their stations and the role of the fixed agents in passing on this information to the corresponding station. Figures 3 and 4 depict the information flow.

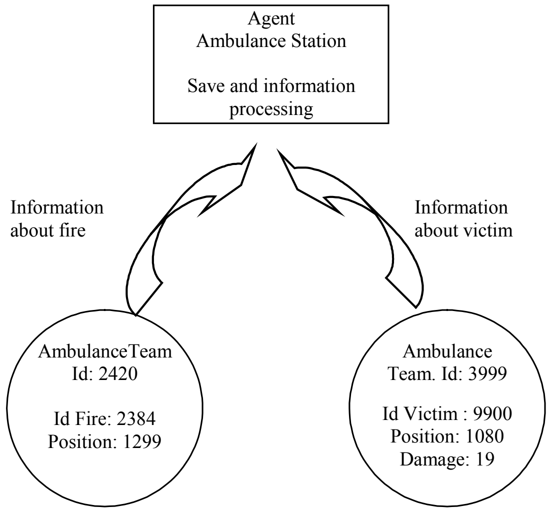

Fig. 3. Information sent to the ambulance station

3.2 Task allocation

When agent stations have information on new tasks, they start the combinatorial auction process. Rescue agents send the central agents their bids corresponding to combinations of tasks to be performed in sequential order. The rescue agents select each activity, taking into account the distance of their location and the place where these are required. Only the activities available in the agents' perception area are taken into account in the bids. In this approach, the rescue agents initially send combinations of the nearest places where it is necessary to perform any task.

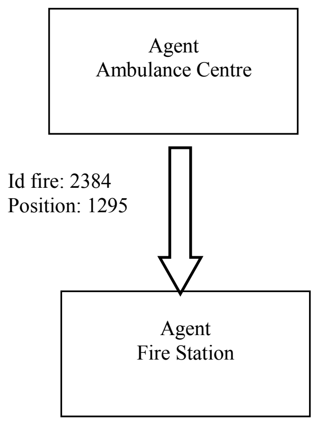

Fig. 4. Information passed from the ambulance to the fire station.

The cost of performing these activities is also included in the bid. It is computed following equation 4, below:

$$\text{Cost estimate} = \sum_i f(Dis, CPT) \quad (4)$$

$$f(Dis, CPT) = Dis * CPT$$

where:

- i = Number of tasks to be performed sequentially.
- *Dis*= Distance from the agent location to the place where the task will be performed.

- *CPT*= Cost of Performing the Task.

For instance, the CPT of the police agent is the cost required for clearing the road that is provided by the Robocup Rescue simulator (property *repairCost* of the blocked road); the CPT of fire brigades is the degree of fieriness (spelt fieryness in the simulator) that specifies how much a building is burning. If the estimated cost of equation 4 is greater that current agent property (hp, damage) and capabilities (i.e., water quantity), the bid cost is set to ∞.

The *f(Dis,CPT)=Dis*CPT* function was defined because both the distance and the cost of performing the task are crucial factors in deciding the overall cost.

All bids received by the central station are processed using the *winner determination algorithm* explained in section 3.2. Tasks are selected by ensuring that sets conform to the maximum number of tasks and the minimum cost. Using the algorithm presented in the previous section, the minimum cost is found, rather than the maximum price.

That is, the winner determination consists of finding the solution that minimizes the following:

$$\min_{W \in A} \sum_{S \in W} \bar{b}(S) \qquad (4)$$

where

$$\bar{b}(S) = \min_{i \in bidders} b_i(S) \qquad (5)$$

4. Example

Let's assume that the fire station has knowledge of four fires in progress in the disaster scenario, identified by 319, 1230, 2500 and 3829; and that there are three fire fighting teams bidding for them (see Figure 5). The set of items to be auctioned is therefore, M={319, 1230, 2500, 3829}. These are the tasks to be performed by fire brigades.

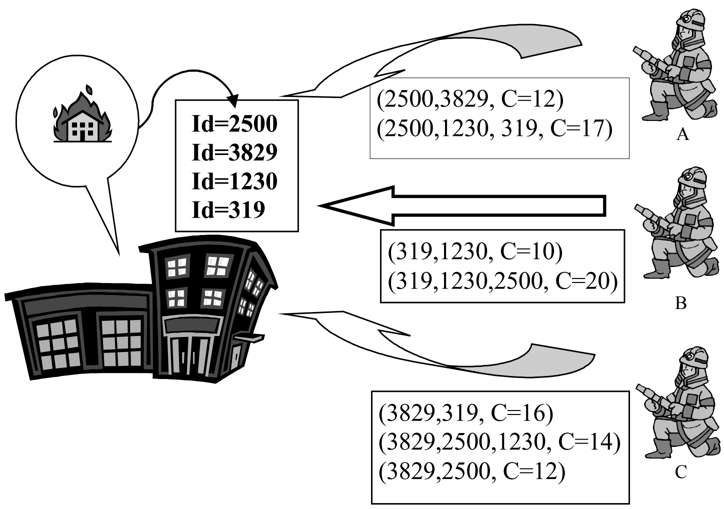

Fig. 5. Fire fighter agents send bids to the fire station

After announcing the tasks, the bids gathered by the fire station are the following:

From agent A:

$B_1=<S_1, b_A(S_1))>$

$S_1 = \{2500, 3829\}$ $b_A(S_1) = 10$

$B_2=<S_2, b_A(S_2))>$

$S_2 = \{2500, 1230,319\}$ $b_A(S_2) = 17$

From agent B:

$B_3=<S_3, b_B(S_3))>$

$S_3 = \{319, 1230\}$ $b_B(S_3) = 10$

$B_4=<S_4, b_B(S_4))>$

$S_4 = \{2500\}$ $b_B(S_4) = 20$

From agent C:

$B_5=<S_5, b_C(S_5))>$

$S_5 = \{3829,319\}$ $\{b_C(S_5) = 16$

$B_6=<S_6, b_C(S_6))>$

$S_6 = \{3829,2500,1230\}$ $b_C(S_6) = 14$

$B_7=<S_7, b_C(S_7))>$

$S_7 = \{3829,2500\}$ $b_C(S_7) = 12$

First of all, we proceed to re-order the different items on each combinatorial auction S, getting the new set of bids shown in the following table.

Bid	S	b
B_1	{2500,3829}	10
B_2	{319,1230,2500}	17
B_3	{319,1230}	10
B_4	{2500}	20
B_5	{319,3829}	16
B_6	{1230,2500,3829}	14
B_7	{2500,3829}	12

We can see that two combinations of items are identical, S_1 and S_7, so the more expensive one S_7 is removed in line with equation (5). The set of bids that make up the winner determination problem is now as follows:

Bid	S	$\bar{b}$
B_1	{2500,3829}	10
B_2	{319,1230,2500}	17
B_3	{319,1230}	10
B_4	{2500}	20
B_5	{319, 3829}	16
B_6	{1230,2500,3829}	14

This is the set of bids that is submitted to the winner determination algorithm, being $W = \{S_1, S_2, S_3, S_4, S_5, S_6\}$.

The search space corresponding to the current data is as follows (Figure 6):

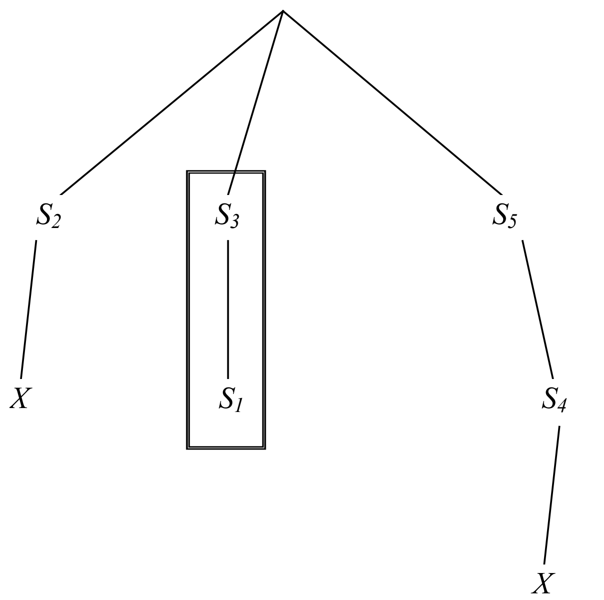

Fig. 6. Search space example

Note that the solution is the path $S_3 \cup S_1$. When applying a heuristic search, S3 is selected as the first node to be expanded since it is the bid with the lowest price. The search tree finally generated is shown below (Figure 7), obtaining the solution $S_3 \cup S_1$:

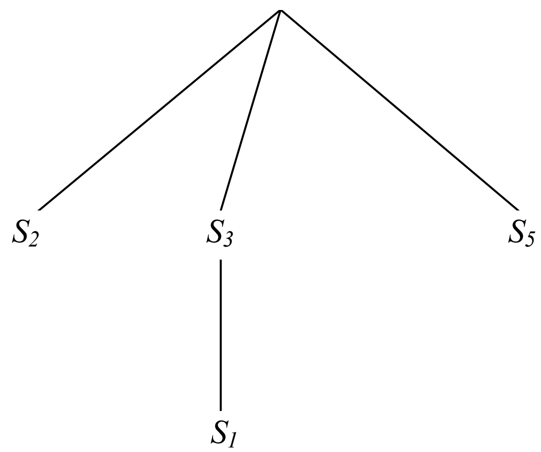

Fig. 7. Search tree example

Conclusions and discusión

In this paper we have presented a task allocation strategy for the RoboCup Rescue scenario based on combinatorial auctions. Task allocation helps us to maximize the benefits obtained from the actions performed by each rescue agent. If each agent maximizes their benefits, it is possible to obtain a better global performance from the rescue teams as a whole. We expect that experimental work will corroborate our proposal. In this sense, we are planning to compare the combinatorial auction techniques presented in this paper against multicriteria decision techniques that we have already developed for the same scenario in [12].

There are some previous works, such as [10] and [11] on applying combinatorial auctions to task allocation. In [10], agents are competing for roles. This is quite a different approach to ours. RoboCup Rescue provides agents with fixed rolesthat cannot be changed. So we concentrate on agent distribution. In [11], combinatorial auctions are used as a strategy for exploring the world of RoboCup Rescue. The approach can be complementary to ours in the task gathering phase.

In future work, we are thinking of modifying the search algorithm for winner determination in order to take into account the sequence of the items in the bids. Precedence constraint on tasks is relevant in rescue operations. Recent works, such as [8] can provide useful insights in this area. Other crucial issues, such as pre-emption also need to be solved, in order to deal with environmental dynamics.

Acknowledgments

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