A Market Based Approach for Complex Task Allocation for Wireless Network Based Multi-Robot System

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Abstract—**Market based approach (MBA) provides communication and coordination for robots in a virtual economy in which they can exchange tasks and resources for payment. Furthermore, trades are enabled via market mechanisms such as auction protocols in which an auctioneer is able to determine the robots best capable of achieving the tasks being offered. In this paper we purpose a modification of MBA for task allocation. This approach consists of auction announcement, bid valuation and submission and winner determination. Several scenarios where robots need to visit particular locations with time and range of wireless network constraints are used for approach verification. Additionally, the results obtained by this approach are compared with results from approach in Control and Coordination of Mobile Motes (CCMM).**

I. Introduction

There is a growing demand for teams of multiple robots to be employed in many application domains. Multi-robot solutions are especially desired for tasks which are too dangerous, expensive, or difficult for humans to perform [2, 5, 11]. These scenarios require the solution of complex problems dealing with scarce resources in highly uncertain and dynamic environments. Due to the nature of these applications, resources must be used efficiently to maximize the benefit of utilizing a multi-robot team. Completing the task in an arbitrary feasible way does not always make a multi-robot solution viable. Existing methods of distributing mission subcomponents among multi-robot teams do not explicitly handle this complexity and instead treat tasks as simple indivisible entities, ignoring any inherent structure and semantics that such complex tasks might have. The information contained within task specifications can be exploited to produce more efficient team plans by giving individual robots the ability to come up with innovative and more localized ways to perform a task or enabling multiple robots to cooperate by sharing the subcomponents of a task [2, 31]. For many problems, teams of robots are capable of better solutions than a single robot. There are several reasons why multiple robots might be preferable [3]:

- Multi-robot teams are capable of increased efficiency by distributing or parallelizing the required workload. For missions that can be broken into largely independent subtasks, individual robots or small groups can simultaneously work on different subcomponents [2, 3, 5].
- Teams are capable of more diversity and innovation in the types of solutions they can achieve. There is an exponential number of ways to distribute tasks among a team. Moreover, robots with different states or knowledge may find or prefer different ways of solving parts of the mission [2, 3, 5].
- Robots with heterogeneous capabilities can work together to produce more flexible solutions. Specialized robots can often find better solutions to the problems for which they are best equipped, in contrast to generalist robots that are more versatile but not as effective at accomplishing every type of task [2, 3, 5].
- Some types of tasks often require multiple robots when a single robot is incapable of performing it alone. Manipulating a heavy object, simultaneous measurement from different locations, or moving in formation cannot be performed by one robot alone [2, 3, 5].
- Having multiple robots can add a level of robustness unavailable in a single robot solution; if one robot experiences a failure the rest of the system can compensate for the loss [2, 3, 5].

II. Aproach Description

In the context of complex missions, the most common approach used in practice involves reliance on a human expert for mission planning, followed by running a simple task allocation algorithm to determine which robot should perform each subtask. However, such approaches—and many others that have been explored—essentially prune out many of the good solutions, and are often only capable of finding highly suboptimal ones. This distinction from the traditional task

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allocation problem recognizes the fact that our coordination problem involves not only determining how to distribute the tasks among the team, but at the same time establishing strategies to achieve them. Our approach to solving the complex task allocation problem is inspired by market-based economic systems. Market mechanisms create an environment within which individual self-interested agents are incentivized to achieve a good system-wide solution. Mechanisms can be viewed as entities that solve a distributed optimization problem specified by separate pieces of input held privately by each agent [4]. The multi-robot coordination problem we address can be cast as one of finding a mechanism that accepts representations of robot states and abilities and outputs a desirable team behavior. After a basic explanation of market-based methods, our auction auctions will be described [2].

A. Market-based Multi-robot Coordination

The idea of using market mechanisms for agent coordination has existed since as early as 1972 with the Distributed Computing System (DCS) [5] and became much more prevalent after the development of the Contract Net Protocol (CNP) around 1980 [6]. In such a system, robots and other agents are designed as self-interested participants in a virtual economy in which they can exchange task contracts and resources for payment (or, in some cases, other tasks [7]). Trades are enabled via market mechanisms such as auction protocols, in which an auctioneer is able to determine the robots best capable of achieving the tasks being offered. Agents in a market-based multi-robot system are designed to behave competitively, despite being teammates in reality. Now, we shall describe TraderBots [8, 31], a specific protocol that we use to incorporate complex tasks. In TraderBots, auctions are held in a peer-to-peer fashion and any agent—called a trader—is capable of taking on the roles of auctioneer and bidder when required. Figure 1 gives a general depiction of the TraderBots auction protocol, essentially an extension of the Contract Net Protocol [7].

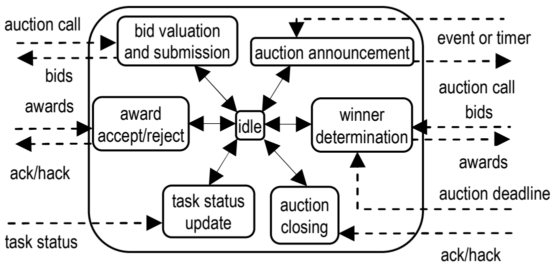

Figure 1: A state diagram of the TraderBots auction protocol. Dashed arrows represent messages and dotted arrows represent other events that trigger transitions into new states.

Our decision to use auctions as a coordination mechanism stems from the existence of several desirable properties of these approaches [3]:

- Efficiency. Auctions are able to produce efficient solutions with respect to a variety of team objective functions [8, 11, 9]. Given an initial solution, auctions can be used as a local search heuristic to improve the solution over time. Sandholm [10] has proven that the optimal solution can be reached in a finite number of auction steps with a sufficiently expressive set of contract types, and Andersson and Sandholm [12] have demonstrated empirically that low-cost solutions can be reached given time limitations and a more restricted contract set. More specifically, their experiments suggest that combinations of single-task and multi-task exchanges perform best in this setting. As will be explained, our approach can be viewed as an auction mechanism containing these two types of contracts.
- Robustness. Market-based approaches can be made robust to several types of malfunctions, including complete or partial failures of robots and limitations of communications infrastructure [13, 14]. Additionally, these systems do not require a central coordinator agent that might create a single point of failure.
- Scalability. The computational and communication requirements of market-based approaches are usually manageable, and do not prohibit these systems from providing efficient solutions as the size of the team or input increases [8]. In the case of combinatorial auctions, although there are an exponential number of task subsets to consider, heuristic approaches to bundle reduction [17, 15, 18, 19] perform well in practice and such auctions can be cleared quickly [20]. A scalability comparison between market-based, behavior-based, and centralized approaches [16] demonstrates that the market approach can provide significantly higher quality solutions than the behavior-based approach while using significantly less computation time than the centralized approach.
- Online input. Auction-based approaches are able to seamlessly incorporate the introduction of new tasks [21, 14, 22, 23, 24] or the deletion of tasks [21], as well as the addition or removal of robots [21, 14].
- Uncertainty. Even with little or no prior information, market-based systems are able to operate in unknown and dynamic environments by allowing individuals to adapt cost estimates over time, and reallocate tasks when appropriate [3, 24].

B. Task Trees

Complex tasks are modeled as task trees. A task tree is defined as a rooted set of task nodes connected by directed edges that specify parent-child relationships between the tasks (Figure 2). Each successive level of the tree represents a further refinement of a complex task: the root is the most abstract description, and the lowest level contains primitive tasks that can be executed by a robot or another agent in the system. Task trees are a generic representation. Constructing a task tree involves performing a hierarchical decomposition on an abstract task. The way in which subtasks are related to their parents can vary depending on application and the degree of coordination desired [31].

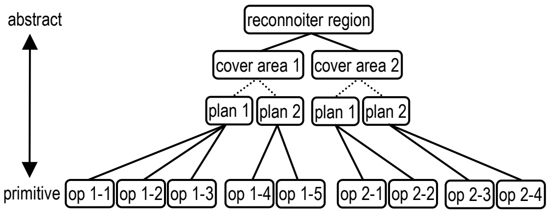

Figure 2: An example AND/OR task tree for an area reconnaissance scenario

- Party Partially ordered tasks. Abstract tasks can be decomposed into a set of subtasks, some of which have precedence constraints [27, 28, 29], simultaneity constraints [30], or time windows. Figure 3 shows an example of a task tree with precedence constraints. Note that the children of an abstract node may be a complex task network related by multiple ordering constraints.
- Multiple robot tasks and tight coordination. Some missions may require certain tasks to be executed by more than one robot with a high degree of cooperation at the execution level.

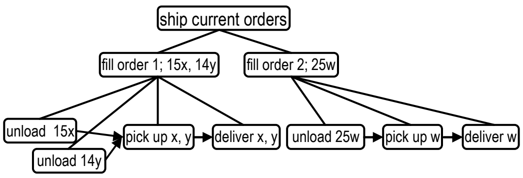

Figure 3: An example task tree for an warehouse shipping task.

C. Task Trees Auctions

Consider putting a complex task on the market through an auction announcement. Assuming that this task can be performed by a single robot, each participant should be able to come up with a valuation for the task by looking at its state, resources, and existing commitments together with the task's requirements. The winner of the auction would be able to decompose the task in whichever way it prefers, as long as it satisfies the requirements. However, it is possible that a better solution might be found if multiple robots perform different subtasks of the complex task. So the system could somehow decompose the task first, and then offer the subtasks on the market. This is not always a prudent approach since it isn't clear how the task should be decomposed to maximize efficiency. These approaches are simply the allocate-then-decompose and decompose-then-allocate. In task tree auctions the goods being traded are generalized from atomic tasks to task trees. This allows contracts to be bought and sold for executing tasks at variable levels of abstraction. A winner of an auction is responsible as a subcontractor to the seller and must ensure that the tasks are completed—either by executing the task itself, or by devising an intelligent subteam plan and subcontracting parts out to other teammates in future negotiations—before receiving payment. In order to generalize the market, several modifications must be made to the baseline auction protocol described previously [31]. Steps are revised as follows:

- Auction announcement. An auction announcement specifies a full or partial task tree, potentially with reserve prices defined for each tree node. Any trading agent representing a robot, operator, or other system resource can hold or participate in a task tree auction. Auctions may be called asynchronously (with the possibility multiple auctions occurring at the same time).
- Bid valuation and submission. The process of bid valuation now includes two phases:
  - Valuation. Each bidder r computes the cost, $c_r^{val}(T)$, of each task T in the tree. If the task is abstract, the bidder estimates the cost of performing the task according to the auctioneer's decomposition specified by the offered tree.
  - Decomposition. For each abstract task T in the tree, the bidder comes up with its own decomposition. Robots may decompose task differently due to differences in capabilities, state, or local information. If the cost of the new decomposition, $c_r^{dec}(T)$, is lower than the bidder's cost for the auctioneer's plan for that node, the that cost is used within the bid. I.e., the bid price for a task T is $b(T) = min\{c_r^{val}(T), c_r^{dec}(T)\}$.
- Winner determination. In general, task tree auctions can be considered a special case of combinatorial auctions; therefore clearing a general task tree is NP-hard [25, 26].

III. IMPLEMENTATION OF MBA

MATLAB, Simulink and TrueTime 1.5 [1] were used for making simulation scenario (Figure 4). The scenario consists of three robots visiting particular locations with time and range of the wireless network constraints. Since CCMM had ability to be used in resolving the scenario problem in terms of constraints, modifications were made to CCMM so that it has MBA. Additionally, the original CCMM and the one with MBA modifications were used for comparisons. The original algorithm in CCMM had the following steps:

- Read new network messages containing information of:
  - Visited nodes.
  - Target of the sending node.
- If (someone has the same target as we do && we have the lowest priority), then change target.

- If (heading to a place that has already been visited), then change target.
- If (arrived at target) then paint the target green && change target.
- Send new network messages to other nodes.

Modifications were made in way of choosing locations needed to be visited and priority

- Each robot computes its distances to locations and uses the shortest one to choose next location to visit.
- Priority is $\frac{1}{value\ of\ shortest\ distance}$.

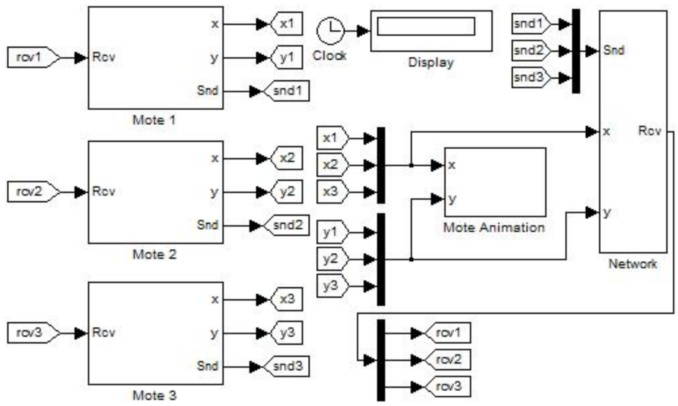

Figure 4: Control and Coordination of Mobile Motes

IV. SIMULATION RESULTS

Before starting the simulation it is necessary to define a matrix of locations needed to be visited and matrix of start positions of robots. Additionally, it is possible to adjust the range of wireless network what is done for approach verification. After starting the simulation, window with graphical presentation appears and shows movement of robots and progress of solution (Figure 5). During the simulation additional information of visited locations, heading of robots and their priority is available to in command window of the MATLAB. The matrix of locations that we use to compare results is:

$$visitPoints = \begin{bmatrix} -18 & -15 & -15 & 0 & 0 & 15 & 15 & 18 \\ 0 & -15 & 15 & -18 & 18 & -15 & 15 & 0 \end{bmatrix}$$

The first and the second row presents X and Y coordinate, respectively. The matrix of starting positions of robots is:

$$robotPositions = \begin{bmatrix} -18 & 18 & 0 \\ -18 & -18 & 15 \end{bmatrix}$$

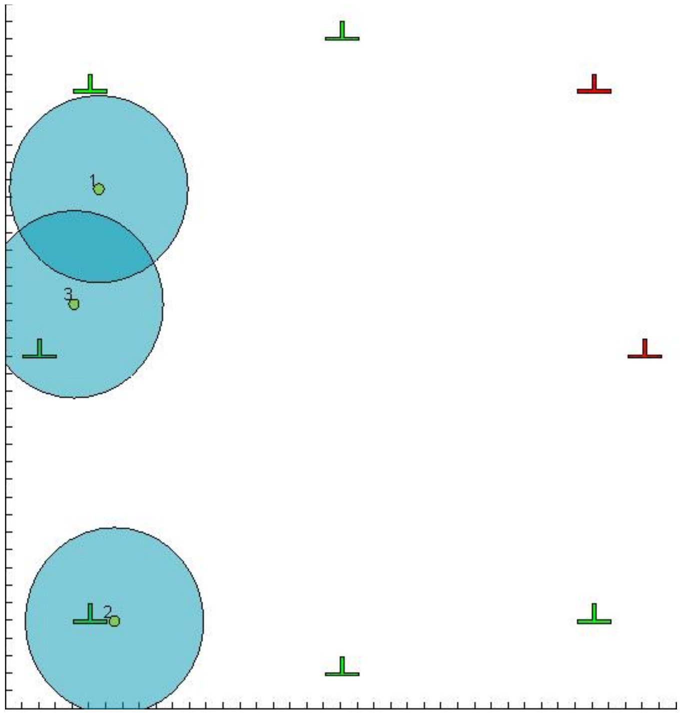

Figure 5: Graphical presentation of simulation

In the Table 1 the results of MBA for task allocation with time and range of wireless network constraints in regards to existing approach in CCMM are presented.

TABLE I. RESULTS OF SIMULATION

Range of wireless network	***MBA approach***	***CCMM approach***
Meter [m]	Time [s]	Time [s]
5.31	25.3	41.3
11.18	19.4	30.5
22.52	15.4	25.4
44.41	13.7	24.8
86.67	13.6	22.6

For the first two cases, where the range of wireless network is relatively small and possibility that some locations could be visited more than once exists (due to disability to inform the robot that the location to which it is heading towards is already visited, see Figure 5) MBA is 38.7% and 36.4% faster than CCMM, respectively. Furthermore, for the last three cases where the range of wireless network is big enough and chance that some locations could be visited more than once don't exists MBA is 39.3%, 44.7% and 39.8% faster than CCMM, respectively.

V. CONCLUSON

Completing the task in an arbitrary feasible way as in existing approach of CCMM does not always make a multi-robot solution viable. As it is shown, the MBA gave much better results because this approach recognizes the fact that our coordination problem involves not only determining how to distribute the tasks among the team, but at the same time establishing strategies to achieve them.

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