Distributed Constraint Optimization for Mobile Sensor Teams

(Doctoral Consortium)

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Coordinating a mobile sensing agents (MST) to adequately position themselves with regards to points of interest generally called targets (e.g., disaster survivors, military targets, or pollution spills), is a challenging problem in many multiagent applications. Such applications are inherently dynamic due to changes in the environment, technology failures, and incomplete knowledge of the agents. Agents must adaptively respond by changing their locations to continually optimize the coverage of targets. Optimally choosing where to position agents to meet the coverage requirements in a static setting is a known NP-hard optimization problem. Doing so in a dynamic distributed environment is a challenging task. In this work I continue to develop and study the DCOP_MST model [2] which is a new model for representing MST problems that is based on the Distributed Constraint Optimization (DCOP) Framework.

DCOP is a general model of distributed multi-agent coordination. A DCOP is constituted of agents, variables, and (soft and hard) constraints between sets of variables that reflect the costs of assignments to the variables. Each agent has exclusive control over a subset of the variables and knows information relevant to its variables, such as the values that can be assigned to them (their domains) and the constraints involving them. The goal is to select an assignment of values to the variables that minimizes the aggregated costs of the constraints. In many ways DCOPs are a natural fit for MST applications, which are inherently decentralized. However, DCOPs fall short in two ways. First, constraints in a MST problem may involve all agents which can result in an exponential-sized constraint structure, which is difficult to solve. Second, DCOP is a static model. In contrast, the coverage problem confronting the agents in realistic applications is highly dynamic. There are three types of dynamism in MST applications: changes in the environment external to the agents, including targets arising, moving, and disappearing, or target coverage requirements being modified by an outside authority; changes inherent to the agents, including sensor failures resulting in targets being missed or false information being disseminated; and changes in the agents' knowledge of the environment, such as the presence of targets and the quality with which they can be sensed from different locations.

In DCOP_MST, agents maintain variables for their physical positions, while each target is represented by a constraint that reflects the quality of coverage of that target. In contrast to conventional, static DCOP, DCOP_MST not only permits dynamism but exploits it by restricting variable domains to nearby locations; consequently, variable domains and constraints change as the agents move through the environment. DCOP_MST confers three major advantages. It directly represents the multiple forms of dynamism inherent in MSTs. It also provides a compact representation that can be solved efficiently with local search algorithms, with information and communication locality based on physical locality as typically occurs in MST applications. Finally, DCOP_MST facilitates organization of the team into multiple sub-teams that can specialize in different roles and coordinate their activity through dynamic events. We demonstrate how a search-and-detection team responsible for finding new targets and a surveillance sub-team tasked with coverage of known targets can effectively work together to improve performance while using the DCOP_MST framework to coordinate.

We propose different algorithms to meet the specific needs of each sub-team and several methods for cooperation between sub-teams. For the search-and-detection team, we develop an algorithm based on DSA that forces intensive exploration for new targets. For the surveillance sub-team, we adapt several well-known incomplete DCOP algorithms, including the Maximum Gain Messages (MGM) algorithm, the Distributed Stochastic Algorithm (DSA) and the Max-sum algorithm which requires us to develop an efficient method for agents to find the value assignment in their local environment, which is optimal in minimizing the maximum unmet coverage requirement over all targets. In order to avoid an exponential constraint network, instead of choosing from among all possible locations, each agent considers only nearby locations. Constraints thus do not need to involve all agents at all times but only the agents who are close enough to possibly cover the target. The disadvantage of dynamic domains based on physical locality is that adaptations of standard local search algorithms tend to become trapped in local optima where targets beyond the immediate range of the agents go uncovered.

To address this shortcoming we develop exploration methods to be used with the local search algorithms. In designing the algorithms that the agents run, we must balance

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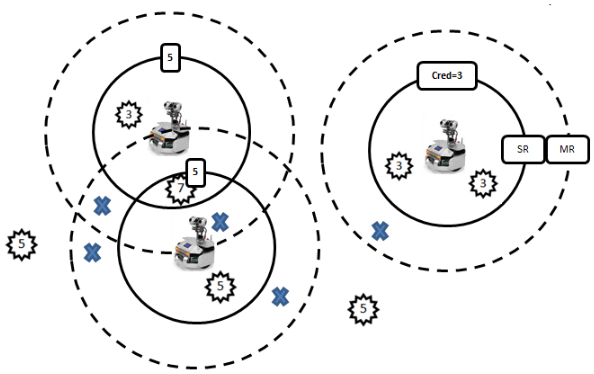

Figure 1: An example of a DCOP_MST problem.

exploration (e.g., finding new targets or better sensing locations) with exploitation (e.g., deciding where to position themselves based on existing information). This tradeoff is complicated by the fact that considering alternative locations is not just an abstract computational step but involves a physical movement to the new location. Our algorithms are extensively evaluated in a simulation environment. The utility that an agent derives from handling a target depends on the agents' proximity to the target and on the agents' credibility (The quality of agents' capabilities). We use a reputation model to determine the individual credibility of agents and consider both additive and sub-modular joint credibility functions for determining coverage of targets by multiple agents.

Agents in DCOP_MST compute new positions using distributed constraint optimization. Both domains and constraints change as the agents move. Due to the dynamic nature of the problem and the large number of possible assignments (even in the reduced DCOP_MST model), complete algorithms are not practical and we focus on incomplete local search algorithms instead. The performance is measured on two objectives: minimizing the maximum remaining coverage requirement, and minimizing the sum of remaining coverage requirements. Our results show that incomplete algorithms with the exploration heuristics outperform the standard incomplete algorithms across a wide range of settings. Furthermore, organizing the team into two sub-teams leads to significant gains in performance, and performance continues to improve with greater cooperation between the sub-teams. Two main tools are developed and used in this research. A software simulator and a robot team simulation. The software simulator allows greater flexibility in problem scale. The robot team is more rigid but provides a more realistic setting for testing the model and the algorithms.

Figure 1 presents a visual representation of a DCOP_MST problem with three agents. Each agent is the center of two circles, a smaller circle which represents its sensing range and a larger dashed circle which represents its mobility range. The number above the SR represents the agent's credibility. The numbers in the star shapes are the significance of the targets. The x-marks represent possible alternative positions. The DCOP_MST model has been implemented and tested by the use of the software simulation tool. The basic scenario is of mobile sensor teams which have to cooperate in an attempt to provide optimal coverage of targets, in a dynamic setting. The experimental study included over 40 different experiments. The experiments could be divided into two clusters. The first involves only surveillance agents and the second involves both search and surveillance agents. Each experiment was designed to test a different aspect of the models' performance. Several factors which were monitored were: 1. Solution quality -Two parameters, which define the quality of a given solution are measured throughout the experiment. The first was the maximal difference between coverage requirement and actual coverage. The second was the sum of differences over all the targets between the coverage requirements and the actual coverage. 2. Speed of convergence- The number of iterations it takes for each algorithm to converge. 3. Number of messages communicated. 4. Average distance traveled. 5. Sensitivity to dynamic events such as additional targets or reduction of credibility. 6. Sensitivity to a changing frequency of events. 7. Sensitivity to changes in the defining parameters such as Sensing Range, Mobility Range and others. 8. Effectiveness of different methods of cooperation between two team of agents with different capabilities. 9. Coverage when the neighbor set is fixed. 10. Number of targets found as a function of the level of exploration. 11. Solution quality in relation to a different ratio of surveillance to search agents.

The agents ran several different algorithms and the performance of the entire team was measured throughout the experiment. The algorithms were: 1. MGM_MST - an algorithm based on the Maximum Gain Messages (MGM) algorithm. 2. DSA_MST - an algorithm based on the Distributed Stochastic Algorithm (DSA). 3. Max-sum_MST - an algorithm based on the Max-sum inference algorithm [1]. 4. MGM_PILR - an algorithm based on MGM which includes greater exploration by a periodic increase of local reduction. 5. DSA_PILR- an algorithm based on DSA which includes greater exploration. 6. Max-sum_PILR- an algorithm based on Max-sum which includes greater exploration. 7. Max-sum_FMR- an algorithm based on Max-sum which incorporates function meta reasoning. It also eliminates the exponential time complexity of Max-sum by bounding the number of agents involved in each constraint. The results indicate that the algorithms which incorporated more exploration converged faster and achieved a better solution ,i.e. closer to the optimal solution.

Based on this study, a paper named: "Distributed Constraint Optimization for Teams of Mobile Sensing Agents" has been submitted to the Journal of Autonomous Agents and Multi Agent Systems (JAAMAS) peer reviewed journal on Jan 2014 and has been accepted for publication. In addition, a paper named "Applying MaxSum to DCOP_MST" was presented at the DCR workshop in the IJCAI 2013 conference and a paper named "Explorative Max-sum for Teams of Mobile Sensing Agents" has been accepted as a full paper in the upcoming AAMAS2014 conference.

1. REFERENCES

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