Applying DCOP_MST to a Team of Mobile Robots with Directional Sensing Abilities

(Extended Abstract)

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ABSTRACT

DCOP_MST is an extension of the DCOP framework for representing and solving dynamic multi-agent applications that include teams of mobile sensing agents. Local search algorithms, enhanced with exploration methods were recently found to produce high quality solutions for DCOP_MST in software simulations. Applying DCOP_MST to robots with directed sensors (e.g., cameras) requires addressing limitations, which were not part of the original design of the DCOP_MST model, e.g., limited angle of the field of vision, collisions between robots etc.

In this paper we contribute to the ongoing effort of applying DCOPs to real world applications by addressing the challenges one faces when applying the DCOP_MST model to a team of mobile sensing robots with directed sensors. We integrate the required adjustments into a new model, DCOP_MST^R, which is the modified version of DCOP_MST for such a real world robot application with directed sensors. The proposed revised model was implemented and evaluated both in software simulations and on a team of robots carrying cameras. Our evaluation of existing algorithms revealed the need to combine actions that change the location of a robot with actions that change its sensing direction in order to achieve effective exploration when solving DCOP_MST^R.

1. INTRODUCTION

Multi-agent systems that include teams of mobile sensing agents have been previously modeled using the Distributed Constraint Optimization Problem (DCOP) framework by representing mobile sensors as agents that need to select locations and their tasks/targets as constraints [2]. Recently, Zivan et al. [5, 3] proposed a model (DCOP_MST) and corresponding local search algorithms for representing and solving such scenarios, particularly focusing on teams of mobile sensing agents that need to select a deployment for the sensors in order to cover a partially unknown environment. DCOP_MST is an extension of the DCOP model that allows agents to adjust their location in order to adapt to dynamically changing environments. The local distributed search algorithms that were proposed for solving DCOP_MST, were adjustments of standard local search techniques, such as Distributed Stochastic Algorithm (DSA) [4], to the model, enhanced by specifically designed exploration methods [5]. Nevertheless, prior to this work, the DCOP_MST model and its corresponding algorithms were only tested on a software simulator and not on a mobile robot team. The task of designing a distributed model for a team of hardware robots is most challenging. Thus, there exists only a handful of studies in which DCOP models were actually used to represent real mobile robots [1, 2]. Inspired by the pioneering work of [1, 2], our paper continues the effort to advance the research on realistic implementations of distributed constraint models and algorithms by applying the DCOP_MST model to a team of hardware robots carrying cameras. We analyzed the challenges that are raised when shifting to a hardware simulation, adjusted the existing models to represent these challenges, designed an algorithm that copes with the adjustments better than existing algorithms and empirically evaluated the model and algorithm both on hardware and software simulations.

Our results indicate that algorithms that performed best when solving standard DCOP_MST problems are not as effective for solving DCOP_MST^R scenarios. Therefore, we designed an algorithm (DSA_PDMR^R) with enhanced exploration abilities, inspired by the *Periodic Double Mobility Range* (PDMR) exploration method proposed by [5]. This algorithm outperformed existing algorithms both in our hardware implementations and in software simulations of DCOP_MST^R.

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2. DCOP_MST^R

In order to face the discrepancies between the DCOP_MST model and the realistic scenario we discussed above, we propose the DCOP_MST^R model (R stands for realistic/robots), whose details are specified next:

- For each agent A_i, Dir_i is the direction in which its camera is currently pointing at.
- The assignment of agent A_i is a pair that includes its position Cur_Pos_i and the direction Dir_i.
- The domain of agent A_i includes all possible moves, e.g, a change of location, or a change of direction.
- For each agent A_i, $Ang_i \in (0, 360]$ defines its angle of vision. A_i can monitor a target T_j only if the distance of target T_j from Cur_Pos_i is not larger than A_i's sensing range (SR_i) and the angle between the line of sight to T_j and Dir_i is smaller than or equal to $Ang_i/2$.
- The reduction in credibility resulting from the distance between the agent A_i and target T_j is determined by the *Linear Credibility Reduction Function* ($lin_{i,j}$).

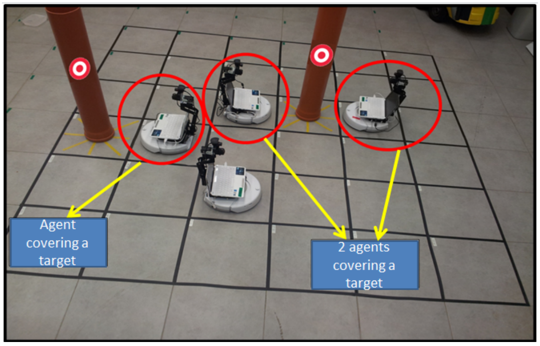

Figure 1: A team of mobile robots with directional sensing equipment covering targets (orange cons).

- Similarly, the reduction in credibility as a result of the angle between the direction the sensor is pointed at and the line of sight between agent A_i and target T_j is specified by the *Lateral Credibility Reduction Function* ($lat_{i,j}$).
- Agents sense a target only if there is no other agent or target in the line of sight between them.
- The effective credibility of agent A_i to target T_j, $Cred_{i,j} = Cred_i \cdot lin_{i,j} \cdot lat_{i,j}$
- Agents are not allowed to be located at the same position.

3. ALGORITHMIC ADJUSTMENTS

The most effective exploration method found in software simulations for DCOP_MST was Periodic Increment of Largest Reduction (PILR), which allows agents to periodically choose a suboptimal assignment, escape local minima and achieve better coverage [5]. Our empirical results indicate that this method does not perform as well when used to solve DCOP_MST^R. The reasons for this difference partly stem from the difference in the domains' content. In DCOP_MST^R a single move changes a relatively smaller part of the local environment. In addition, due to the dependency on the direction, the exploration must be more accurate. Finally, the discretization of turn angles requires a combination of action to be taken to achieve optimal coverage in certain cases.

Thus, we propose an adjusted version of the PDMR exploration method described in [5] for DCOP_MST^R. In DCOP_MST, PDMR allows agents to periodically consider assignments within twice their mobility range (MR). In DCOP_MST^R we adjust PDMR so that agents consider a combination of up to two actions e.g., a move forward and a turn assignment.

4. EXPERIMENTAL SECTION

We conducted experiments both on a team of hardware robots and on a software simulation of the model. The robots chosen for this system were iRobot Creates mounted with Asus laptops equipped with PrimeSense sensors (Figure 1). The setting for the hardware experiment included 6 agents. The agents along with 3 targets were randomly located on a 10 by 10 grid. The targets had importance of 100 and the agents had credibility of 60. The algorithms ran for 15 iterations while at the 7th iteration we simulated a target movement. Each reported result in the graphs in Figure 2 is an average over 10 runs of the algorithm on different randomly generated problems. The results in Figure 2 indicate clearly that DSA_PILR does not have the same level of success as it had when solving standard DCOP_MST [5]. On the other hand DSA_PDMR^R offers a significant improvement over both DSA and DSA_PILR.

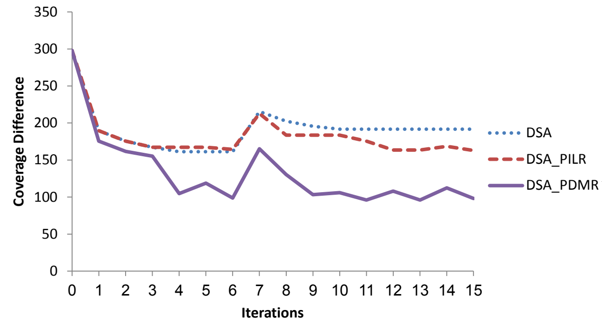

Figure 2: A comparison of the algorithms' performance on the robots. 3 targets, 6 robots.

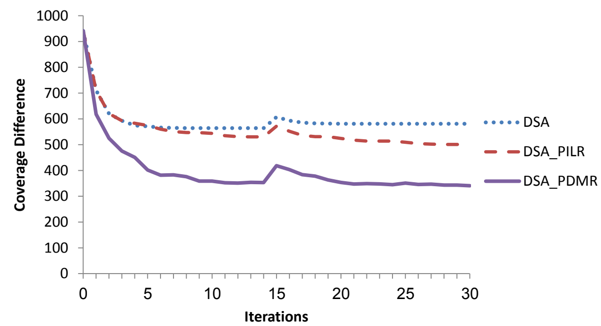

Figure 3: A comparison of the algorithms' performance on the simulator. 10 target, 20 agents.

Software simulations allowed the investigation of larger scenarios. The experiments in Figure 3 included 20 agents and 10 targets that were randomly located on a 20 by 20 grid. Each reported result is an average over 50 runs of the algorithm on different randomly generated problems. it is apparent that, like in the hardware experiment, DSA_PILR offers a very small improvement over DSA for DCOP_MST^R. The DSA_PDMR^R version that we proposed in this paper offers a more significant improvement.

Acknowledgments

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