Towards Designing Multi-Agent Coverage Systems Capable of Anticipation and Tight Coordination with Detailed Environmental and Perception Models

Main Track Extended Abstract

Loïs Vanhée
GREYC
Caen, France
lois.vanhee@unicaen.fr

Laurent Jeanpierre
GREYC
Caen, France
laurent.jeanpierre@unicaen.fr

Abdel-Illah Mouaddib
GREYC
Caen, France
abdel-illah.mouaddib@unicaen.fr

ABSTRACT

This paper introduces a new approach for modelling coverage problems, capable of taking into consideration 1) evolving points of interest, 2) environmental dynamics, including the influence of agent actions, and 3) detailed perception models. Such coverage problems requires tight coordination between agents while anticipating the consequences of their actions for maximizing the covered areas over time while avoiding adverse situations (e.g. collisions).

KEYWORDS

Distributed problem solving; Single and multi-agent planning and scheduling; Multi-robot systems; Human-robot/agent interaction

ACM Reference Format:
Loïs Vanhée, Laurent Jeanpierre, and Abdel-Illah Mouaddib. 2018. Towards Designing Multi-Agent Coverage Systems Capable of Anticipation and Tight Coordination with Detailed Environmental and Perception Models. In *Proc. of the 17th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2018), Stockholm, Sweden, July 10–15, 2018,* IFAAMAS, 3 pages.

ACKNOWLEDGEMENTS

This research was funded by the ANR project: ANR-14-ASTR-0018.

INTRODUCTION

After disasters or during conflicts (e.g. fire, chemical spill, warzone), rescuers often need to travel urgently within hazardous areas (e.g. for evacuating victims). Moving out of such areas requires extra caution for avoiding threats. As illustrated in Figure 1, mobile robots can be deployed as support for augmenting the sensory capabilities of rescuers, in order to watch for surrounding threats, without introducing more humans into the harmful situation. The *number of robots and the time for completing the mission are both strongly limited*, given the amount of space to cover. Furthermore, *the Areas of Interest (AoI) to be covered evolve over time*, as the threats to be watched for change with rescuers' moves.

Four *key features* are critical for deploying such multi-robot systems: 1) *coordination capabilities*, for maximizing the benefit of using multiple robots (e.g. avoiding crashes, avoiding unnecessary observation overlaps); 2) *detailed environmental model*, for tight

Proc. of the 17th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2018), M. Dastani, G. Sukthankar, E. André, S. Koenig (eds.), July 10–15, 2018, Stockholm, Sweden.

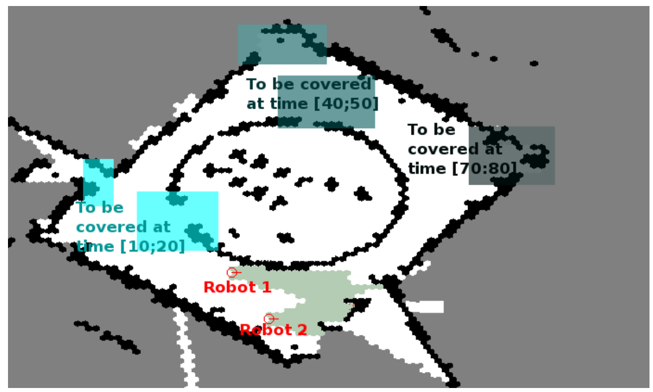

Figure 1: A rescue-support example: the robot team must cover the various Areas of Interest (AoI) at given timesteps. For best covering all the AoI, robots should tightly coordinate for positioning themselves in order to best share the AoI at time [10,20]. Then, robots should split, one for being in time for covering the top [40-50] AoI and the other for covering the [70-80] AoI.

optimization that considers in details robot moving and sensing capabilities (e.g. partially overlapping observations, robot speed) and consequences of robot actions (e.g. collisions); 3) *planning capabilities*, for anticipating the evolution of AoI and consequences of decisions (e.g. being slightly less effective now for being far more effective later); and 4) *coverage optimization capabilities*, for maximizing the coverage of AoI while taking into consideration environmental constraints. Altogether, these features requires to exploit the full potential of the multi-robot system for tightly maximizing the coverage of the AoI over time.

Available multi-agent coverage formalisms fail to integrate these key features altogether, as summarized by Table 1. Complete coverage [7] (i.e. deploy the least amount of sensors for observing all AoI), sweeping [2] (i.e. observe each AoI at least once), sensor barriers [7] (i.e. growing secured perimeters), and reactive node placement [7] (i.e. pattern-based movement, force-repulsion mechanisms) fail to plan ahead and reason about available resources for covering AoI over time. The Dynamic Vehicle Routing Problem [6] (i.e. minimize the cost for visiting a set of nodes) and the Team Time-Window Orienteering Problem [3] (i.e. maximize the reward from visiting a set of nodes within bounded time-frame and total time) integrate planning features, but they rely on environmental models that are too simplistic for modeling environmental dynamics and coverage aspects such as partially overlapping observations or collisions. The Maximum Coverage Problem [4, 5] searches for the observation stances that maximize the coverage of the robot team, with detailed perception models. However, this problem only models one-shot placement, disregarding the evolution of AoI over time and environmental dynamics (i.e. assuming negligible robot moving time with regards to the time constraints).

This paper introduces our current progress for handling these limitations. We are currently expanding the Maximum Coverage Problem for integrating time dynamics. This problem introduces a relevant and highly-exploited structure for modeling multi-robot perception. By adding the notion of time dynamics to this problem, we aim to cover the four features introduced by this article.

TOWARDS A FORMALIZATION

As a formalization, we expand the classic maximum coverage problem with a Finite State Machine (FSM). Basically, each state of this FSM consists of a tuple of observation stances, representing the observation stances in which each robot should be at a given time. The alphabet of this FSM represents the set of combined actions for all robots (e.g. robot 1 turns North, robot 2 moves forward). The transition function represents the consequences how the combined robot actions impact their observation stances. This function can capture aspects such as collisions between robots or evolutions in the environment, possibly caused by robots. Finally, we associate a profit function per round based on the maximum coverage representation of profit function, which models the dynamic evolution of AoI. Such functions capture aspects such as decreasing rewards due to overlapping views and noise related to line of sight and sensor ranges. The problem consists in finding a trajectory in this FSM, given timed-profit functions, that maximizes the total acquired reward over time, starting from the initial state of the system.

CONSIDERED ALGORITHMS

We are developing a new set of algorithms for solving this problem, both efficiently and optimally, as adding the notion of time dynamics entails a deep paradigm shift with regards to the classic "one-shot optimization problem" that is the maximum coverage problem. An optimal algorithm searches for an optimally-rewarding path in the FSM, by relying on a graph-search on a time-based expansion of the FSM that models dynamics. Approximate algorithms expand the classic approximate planning algorithms searching for local optimum (e.g. optimizing the reward that each agent can acquire having set the actions of other agents).

Table 1: Comparing multi-agent coverage approaches

Method	Coordination	Detailed environmental model	Planning	Maximizing Coverage
Complete coverage	✓	✓	✗	✗
Sweeping	✓	✓	✓	✗
Sensor barrier	✓	✓	✗	✗
Reactive node placement	✓	✓	✗	✗
Vehicle Routing	✓	✗	✓	✗
Team Orienteering with Time Window	✓	✗	✓	✓
Maximum Coverage Problem	✓	✓	✗	✓

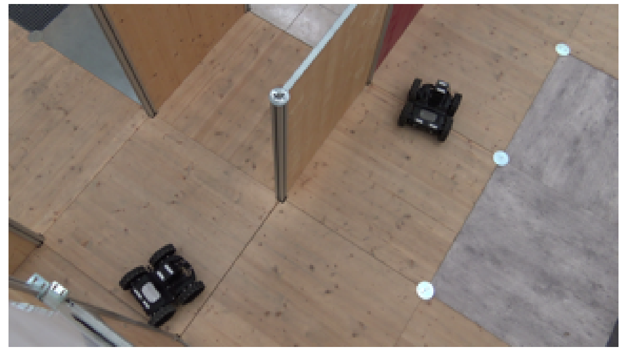

Figure 2: We aim to deploy the dynamic coverage system on a multi-robot system for covering rescuers as they move around a realistic arena

MEANS FOR EVALUATION

For the sake of evaluating these algorithms, we are considering a set of simulated experiments. One of these considered is based on covering a rescuer which crosses a corridor. The robots should anticipate the move of the VIP, for best following him/her along the path. Furthermore, robots should coordinate, in order to split their duties: one following the rescuer for covering the immediate VIP's surroundings, one staying at the entrance of the corridor for covering the rescuerâĂŹs back, one speeding up for covering the exit of the corridor that the VIP will reach. Our preliminary results highlight that the system is capable of automatically generating the desired high-level behaviors, as depicted in the caption of Figure 1.

We are also evaluating the relevance of the new problem as a whole, by integrating it within an actual multi-robot system, as depicted in Figure 2, for covering applications such as the one presented in Figure 1. Basically, system users can draw a set of AoI they want the system to cover at given time periods and then the system should find on its own how to best cover this set over time. This system is to be used for marking possibly harmful areas that surround the rescuers and have these AoI (best) covered by the robots while the rescuers are making their way to the exit, considering their time constraints on rescuer move to the exit.

CONCLUSIONS

Altogether, the proposed formalization, algorithms, and deployment highlight that designing coverage systems capable of anticipation, tight-coordination, and integration of detailed environmental models is technically feasible and can lead to relevant multi-robot applications. Notably, many applications in which the maximum coverage problem has been deployed can benefit from integrating the notion of time and environmental dynamics. For instance, building a k day trip that maximizes the coverage of AoI from [1], can benefit from taking into consideration environmental dynamics, such as weather and crowd forecast, or travelers' exhaustion.

REFERENCES

[1] Igo Brilhante, Jose Antonio Macedo, Franco Maria Nardini, Raffaele Perego, and Chiara Renso. 2014. *TripBuilder: A Tool for Recommending Sightseeing Tours.* Springer International Publishing, Cham, 771–774. https://doi.org/10.1007/978-3-319-06028-6_93

[2] Jan Faigl, Miroslav Kulich, and Libor Preučil. 2011. A sensor placement algorithm for a mobile robot inspection planning. *Journal of Intelligent & Robotic Systems* 62, 3 (2011), 329–353.

[3] Aldy Gunawan, Hoong Chuin Lau, and Pieter Vansteenwegen. 2016. Orienteering problem: A survey of recent variants, solution approaches and applications. *European Journal of Operational Research* 255, 2 (2016), 315–332.

[4] Dorit S Hochba. 1997. Approximation algorithms for np-hard problems. *ACM Sigact News* 28, 2 (1997), 40–52.

[5] G L Nemhauser, L A Wolsey, and M L Fisher. 1978. An analysis of approximations for maximizing submodular set functions—I. *Mathematical Programming* 14, 1 (1978), 265–294. https://doi.org/10.1007/BF01588971

[6] Victor Pillac, Michel Gendreau, Christelle Guéret, and Andrés L Medaglia. 2013. A review of dynamic vehicle routing problems. *European Journal of Operational Research* 225, 1 (2013), 1–11.

[7] Bang Wang. 2010. *Node Movement Strategy.* Springer London, London, 155–171. https://doi.org/10.1007/978-1-84996-059-5_8