Multi-Robot Simultaneous Coverage and Mapping of Complex Scene

Demonstration

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ABSTRACT

In this demonstration, participants will explore a system for multi-robot observation of a complex scene involving the activity of a person. Mobile robots have to cooperate to find a position around the scene maximizing its coverage, *i.e.* allowing a complete view of the human skeleton. Simultaneously, they have to map the unknown environment around the scene. We developed a simulator that allows to generate an environment, a scene, and to simulate robots' observations and motion. During the demo, users will be able to test our simulator, including setting up a scenario and a decision algorithm, monitoring the movements, observations and maps of the robots, and visualizing the performance of the team.

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1 INTRODUCTION

In this demonstration paper, we focus on complex scene observation by mobile robots in unknown and cluttered environments. The robots have to coordinate themselves to explore the environment and to optimize their positioning around the scene so as to maximize the quality of the scene observation. This concerns for instance assistance, rescue and surveillance tasks. We consider that the robots observe a person carrying out an activity in a quasi-static location (scene). We assume that robots are homogeneous, can communicate and know only the relative location of the scene to observe. They have to deploy themselves around the person with the objective to fully observe its pose (*i.e.* the set of skeleton joints), as illustrated in Fig. 1.

Recent works proposed various solutions to coordinate robots in tracking a set of (mobile) targets [1, 3, 6]. However they generally consider that the environment is free of obstacles, or they are too few to obstruct the observation. Yet in distributed recognition scenarios, a particular challenge is when each individual point of view does not allow a satisfactory recognition, *e.g.* because of the presence of occlusions. Thus the robots have to coordinate to obtain the most complementary observations.

Our work focuses on multi-robot scene observation in unknown and cluttered environment. So the robots have to explore and map the environment while simultaneously searching for an optimal joint position around the scene that maximizes the coverage (observation) of the targets. To this end, we proposed an original approach based on a circular topology and an incremental mapping, that has been implemented and validated with a fleet of real robots [4]. We also developed a simulator that allows to generate an environment and a scene, and to simulate robots' observations and motion. By using this simulator, we were able to compare different algorithms for the simultaneous exploration of the environment and coverage of the scene. These results are detailed in the accompanying publication to this demonstration [5].

In this paper, after a brief presentation of the proposed approach and techniques involved, we will focus on describing our simulator, the demonstration workflow and its interactive aspects with the audience[1].

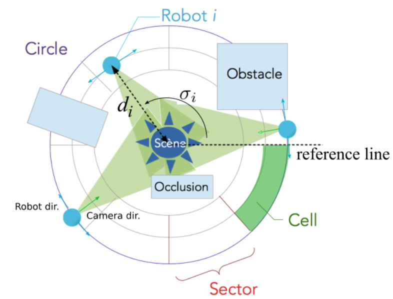

Figure 1: Joint observation of a scene with 3 robots and a navigation model with 2 circles and 8 sectors.

2 OUR APPROACH

Coverage task: To formalize the coverage task of a complex scene observation problem, we use the CMOMMT[2] framework [6]. It aims to dynamically position robots to maximize the coverage[3] of mobile targets. In our problem scenario, robots have to cover a human pose (skeleton) defined as a set

[1] A video is available at https://liris.cnrs.fr/crome/wiki/doku.php?id=demoaamas2018.
[2] Cooperative Multi-robot Observation of Multiple Moving Targets
[3] Here it is defined as the number of targets under observation and the duration of observation of each target.

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of joints (targets). The observation vector of a robot is then defined as a binary vector, where each element is 1 if the robot is tracking the target or 0 otherwise. The individual (resp. joint) observation quality made by a robot (resp. a team) is the average number of joints tracked by the robot (resp. the team). To quantify the individual contribution of a robot to the joint observation, the contribution of a robot is the part of the observation that it is the only one to see.

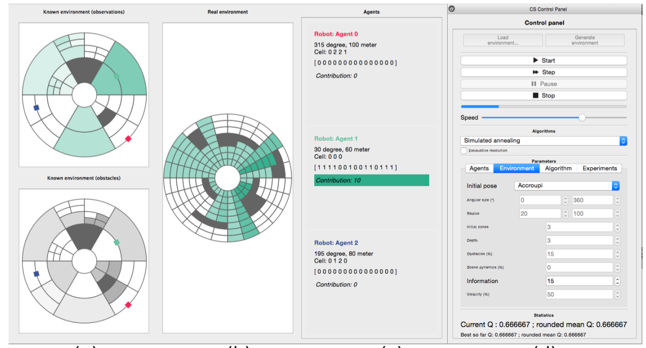
Mapping task and circular topology: As the environment is unknown, robots must build a map to locate themselves and learn observation qualities from different locations. So we extend the CMOMMT framework with a simultaneous mapping task. The map uses cells as a discrete representation of the robots' positions. These cells arise from sectors and concentric circles around the scene where the robots are moving (cf. Fig. 1). This circular navigation topology is adapted to the continuous observation of a scene.

Incremental mapping: One issue of our coverage and mapping problem is the trade-off between exploitation and exploration, that is moving to optimize the coverage versus exploring the environment to find new interesting observation positions. To master the complexity of the state space and the time to explore it, we propose an incremental mapping based on a quadtree structure. The idea is to refine the discretization by splitting cells only in interesting areas *i.e.* where the quality of observation is promising. Fig. 2(a) shows a quadtree map constructed by robots. Two views are given to visualize the different map data: coverage data on the top map with cell qualities in shades of green (the greener the cell, the better is the quality from this cell; white is for cells where the scene is not visible, dark for obstacle cells); obstacle probabilities in shades of grey on the bottom map.

Decision algorithms: We propose different algorithms to guide the robots exploration of the state space. They rely on local versus global information and lead to solutions with different computational and memory costs. Approaches based on local information and meta-heuristic optimizations obtained better results than the exhaustive exploration[4].

3 SIMULATOR

We developed from scratch a simulator (cf. Fig. 2) with two goals: (i) to run a large quantity of experiments in order to compare our different algorithms, (ii) be realistic enough to properly model key features of real mobile robots, environments and scene. First we consider that **robots' motion** around the scenes is perfect. *i.e.* robots can move along circles without trajectory errors, and robots are equipped with sensors allowing them to remotely detect nearby obstacles. **Communications** between robots are also supposed to be instant and errorless. We use **a reference environment** to simulate obstacles and observation of the scene from each cell. The robots do not have access to this environment. They build the quadtree map (cf. Fig. 2(a)) during their exploration. To **generate this reference environment**, one can choose where to put obstacles by loading a file or random ones according to a probability. To **simulate a scene** and assign observations to each cell, one can choose random observations or **real skeleton data**. They have been obtained from human pose captures with Kinect sensor and OpenNI/NITE skeletal tracking library [2]. These data have been imported in the simulator to generate the observation vectors (composed of 15 body joints) for each sector. Fig. 2(b) shows a reference environment with obstacles (black cells), occluded cells (white), and cells with different observation qualities (shades of green)[5]. We add **noise** to the perception from a cell to simulate camera sensor noise and occlusions by other robots[6]. So the observation perceived by a robot from a cell may vary from the reference environment. One important feature of our simulator is that its main parts (data structures (*e.g.* cell, quadtree), decision algorithms, interface) are used both in simulation and for real robots experimentation [4, 5].



(a) (b) (c) (d)

Figure 2: Simulator interface. (a) Quadtree map built by 3 robots (b) Reference environment (c) Monitoring of the 3 robots (d) Setup and control

4 DEMONSTRATION

During the demonstration, participants of the conference will be given the opportunity to configure and observe examples of how a team of robots simultaneously map and cover a human pose and its surrounding environment. The demonstration sequence will be divided into two parts: the configuration of the scenario and the monitoring of the execution. First, the user can choose via the setup panel (cf. Fig. 2(d)) an environment, a human pose, the number of robots and their initial position, the noise degree, the algorithm and its parameters, ... Then, he/she can launch and control the robots' execution via the control panel (cf. Fig. 2(d)). During this phase, the user can observe the movement of the robots and the map they are building (cf. Fig. 2(a)), and have access to information specific to each robot (its current observation vector and its contribution) (cf. Fig. 2(c)). Some statistics concerning the team are also displayed (current joint quality, best joint quality found so far, ...). Finally, a video of our experiments with real robots (Turtlebot2) will be shown.

[4] For further details, see the accompanying publication [5].

[5] The greener the cell, the better is the observation quality.

[6] A noise parameter defines the probability for each value of an observation vector to be flipped compared to the reference values.

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