Decentralized Multi-Robot Coordination for a Risky Surveillance Application

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Abstract

Autonomous robotic systems can play an important role in the automated surveillance of high-risk areas, as they provide a way of keeping humans out of the danger zones. However, in general it is impossible for one agent to cover the whole inspection area, which means that a team of units needs to be deployed. In this case, these robotic agents need to interact tightly, to act as a collaborative team towards the common of securing the whole area to be patrolled.

In the application envisaged in this paper, the main goal for the robot team is to guard the perimeter of a military camp in a hostile environment. The camp is approached (attacked) by multiple enemy forces and the robotic team agents must be capable to detect and neutralize these enemies. . The position and movement of these enemy forces is a priori unknown and they can only be detected when they are within the sensor range of one of the team members.

The proposed multi-robot control methodology is based on a behavior-based control framework. In this behavior-based context, the robotic team members are controlled using one of 2 mutually exclusive behaviors: patrolling or intercepting. In patrol mode the robot seeks to detect enemy forces as rapidly as possible, by balancing 2 constraints: the intervention time should be minimized and the map coverage should be maximized. In interception mode, the robot tries to advance towards an enemy which was detected by one of the robotic team members. Subsequently, the robot tries to neutralize the threat posed by the enemy before enemy is able to reach the camp.

The proposed methodology was tested with good results in a simulation environment with robotic teams with a varying number of members. An added benefit is that by varying the number of robotic team members and by analyzing the resulting intruder interception capacity of the global team, human decision makers can get an idea of the minimum number of robots required to detect enemy forces and safeguard the camp.

Introduction

The multi-robot-collaboration task goes out from a scenario where it is the main goal of the robot team to guard the perimeter of a military camp in a hostile environment. The camp is approached (attacked) by multiple enemy forces and the robotic team agents must be capable to detect and neutralize these enemies. . The position and movement of these enemy forces is a priori unknown and they can only be detected when they are within the sensor range of one of the team members. In this scenario, a large rural environment is considered, as shown on Figure 1a. The black areas on this top-view map represent obstacles (buildings, walls, trees), whereas the gray areas indicate the height of the terrain. The camp area can be identified clearly in the centre of the terrain map.

Control and coordination of multiple robots is a research field which has received a lot of attention during the past 2 decades, generally using some kind of exploration scenario, e.g. in the context of a mapping [2], search and rescue [3] or surveillance [4] application. An important research area is the optimization of the multi-robot formation. In nature, formation control benefits the animals that make use of it [5]. By grouping themselves, animals combine their sensors to maximize the chance of detecting predators, as such minimizing the encounters with predators [6]. Inspired by these biological examples, roboticists have applied similar formation control approaches to artificial agents [7]. In robotic systems, the control task is in general decomposed into a set of behaviors, following the paradigm for behavior-based robotics [8][9]. Also in this paper, we use a behavior-based control strategy. When

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reviewing the state of the art on multi-robot control, one recurring constatation is that most experiments take place in an indoor scenario. The indoor setting facilitates the control problem, as certain issues such as the roughness of the terrain do not need to be taken into account [10]. In [11], Madhavan et al. present an approach towards distributed multi-robot control for localization and mapping in an outdoor environment, taking into account uneven outdoor terrain. In this paper, we present a methodology which takes into account the roughness of the outdoor terrain, but we use it in a different context of formation control for patrolling.

Methodology

An important aspect of this patrol behavior is that enemy forces should not be able to predict the movements made by the robots, so there must be a certain randomization in the robot control. This randomization is achieved by selecting for each robot a number of discrete positions where the robot could go next. These discrete points are selected by considering the current robot orientation and setting up a Gaussian distribution with a mean centered at the current orientation and a standard deviation of 0.5 radians. Random new orientations are then sampled from this Gaussian distribution and for each of the chosen orientations the corresponding Cartesian coordinates are calculated. Conceptually, this means that we extrude a number of candidate points using a Gaussian distribution, taking into account the current robot position and orientation.

The number of randomized candidate points can be chosen at will. Here, a selection of 20 candidate points was made. All these candidate points are then pre-filtered for points lying out of the simulation area or inside obstacles or inside the base camp (it is no use to search for intruders over there). Another aspect which is checked at this stage is whether the robot movement proposed by the candidate point would not bring the robot into a position where the communication with the other robots (and the base station) would be lost. If this is the case, the candidate point is also rejected.

The remaining candidate points are subjected to an optimization strategy. The objective of this optimization scheme is to *minimize the mean intervention time* and to *maximize the global coverage*, as explained in the following paragraphs. The combined robot behavior then aims to balance these both constraints by taking a weighted mean of both movement proposals.

A first objective for the multi-robot team in the patrol behavior is that when a new intruder appears somewhere on the map, it should be possible to intercept this intruder before it is able to breach the camp perimeter. Formally, this can be formulated as an objective to minimize the mean intervention time to each point on the map for all robotic agents.

Practically, this is implemented by storing for each robot a so-called *Intervention Time Map*. The Intervention Time Map stores at each point the time the robot requires for reaching this point from its current position, taking into account the robot speed. The individual intervention time maps of all robots are then overlaid to compose a global intervention time map for the whole system. Figure 1c shows such a global intervention time map for a number of robots. On this figure, the blue areas indicate short intervention time intervals, the red areas indicate zones requiring a large intervention time, which is to be avoided.

During navigation, these intervention time maps are used to estimate the optimality of each of the new candidate positions. Therefore, for each of robot the candidate positions, a new intervention time map is integrated and fused with the intervention time maps of all other robots. This leads to a new global intervention time map as indicated on Figure 1c. We then calculate the mean value of this map, which is said to be the mean intervention time. This process is repeated for all candidate positions and the candidate position leading to the minimal mean intervention time is considered to be the optimal location to move to in order to minimize the global intervention time.

The approach towards map coverage maximization is the information maximization approach described in [12]. The basis for this approach is the construction of a local coverage map. With each scan of its enemy detection sensors, each robot stores the returned sensor data in such a local coverage model, by storing the value ”1” in all cells which have been “viewed” by the robot sensors. The visibility model employed here takes into consideration possible occlusions due to obstacles.

$$CoverageMap(i,j)=\begin{cases}1 & if\ \ Visible(i,j)\\ unchanged & if\ \ !Visible(i,j)\end{cases}$$

At each iteration of the simulation, the information in the coverage model is “aged” by multiplying all entries of the local coverage map with a value between 0 and 1 (in practice: 0.99). The purpose of this approach is to represent the unreliability of “old” data. Indeed, it is very well possible that there was no intruder present in a certain cell at time $t=t_k$, but that does not mean that this situation will necessarily stay like this eternally. Intruders can move and can hide in buildings where the robots cannot detect them, such that it is very well possible that at time $t=t_{k+1}$, there will be an intruder present in the same cell. Therefore, the coverage data recorded in the coverage map cannot stay static as well; it must be decreased at each iteration. Figure 1b shows the effect of the coverage map ageing, by showing the integrated coverage map after a number of iterations. The brighter colored areas on this figure represent zones which have been viewed by a robot in the past, but which are currently not in the visibility field of any robot. As such the information which was gathered there some time ago cannot be trusted completely and – as the data becomes older – it becomes more and more likely that a robot will return there to re-check the gathered data.

For navigation, each robot then analyzes its local coverage map and calculates for each of the candidate points, representing a move to be made, leading to a new position $\boldsymbol{x}$, the amount of cells already covered, taken into account the visibility model at location $\boldsymbol{x}$:

$$Score_{Coverage}(\mathbf{x})=\sum_{Visible(\mathbf{x})} CoverageMap^2$$

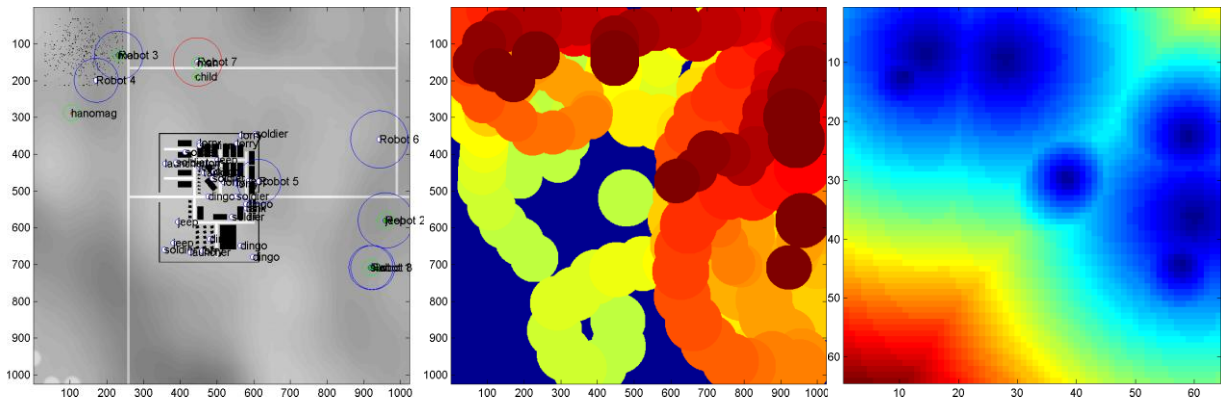
The new location $\boldsymbol{x}$ where $Score_{Coverage}(x)$ is minimal is the point where the most new information can be possibly gained when advancing to this location. Otherwise put, the point $\boldsymbol{x}$ maximizes the information gain and is thus the best place to go to detect intruders.

Results

In this section, the results of the presented control methodology are analyzed. Therefore, the Figure 1 shows:

- On the Left: A top view digital elevation map of the environment, indicating obstacles in black and roads in white. Friendly units are indicated as white circles. Active friendly agents are indicated with an extra blue circle, indicating their field of view. Enemy agents are shown as red dots with a blue circle, indicating their field of view. The size of the indicator of the enemy agents increases as the move forward to attack the camp, while it turns to green once they are neutralized.
- In the Middle: The Global Coverage Map, showing in blue, unseen areas and in brown visible areas. Brighter areas represent zones which have been visited in the past.
- On the Right: The Global Intervention Time Map. Blue areas indicate short intervention time intervals, the red areas indicate zones requiring a large intervention time

From Figure 1, it can be noted that the active robotic agents were able to intercept all intruders before they were able to reach the camp. Of course, this is not possible for all parameter configurations. The benefit of this simulation is that it can provide decision makers a founded benchmark on the number of agents to deploy as a function of the expected enemy troop force.



a) Top View Robot Map   b) Coverage Map   c) Intervention Time Map

Figure 1: Final phase of the Camp Surveillance scenario simulation

Conclusions

In this paper, we have presented a decentralized control strategy for multi-robot coordination for a camp patrol scenario. Using the presented multi-agent control architecture, it is possible to make teams of robots execute a well-defined task in a challenging environment. To achieve this, a behavior based framework was implemented, incorporating a novel multi-robot control strategy. This strategy considers the optimal placement of a team of robotic agents to minimize the global intervention time and to maximize the map coverage. The algorithm presented here for multi-robot coordination was shown to achieve good results and to scale well with increasing the number of robots.

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