Line-of-Sight Constrained Exploration for Reactive Multiagent Robotic Teams

Ronald C. Arkin
College of Computing
Georgia Tech
Atlanta, GA, U.S.A. 30332
(404) 894-8209
arkin@cc.gatech.edu

Jonathan Diaz
College of Computing
Georgia Tech
Atlanta, GA, U.S.A. 30332
jdiaz@cc.gatech.edu

ABSTRACT
In this paper we investigate how a team of robotic agents can self-organize for the exploration of a building subject to the constraint of maintaining line-of-sight communications. Three different behavioral strategies (anchored wander, quadrant-biased anchored wander, and informed exploration) have been developed and tested in simulation. The results are demonstrated within the context of the MissionLab multiagent mission specification system on two different scenarios.

Keywords
Algorithms, multiagent robotic systems, navigation, line-of-sight robot communication.

1. INTRODUCTION
The Georgia Tech Mobile Robotics Laboratory has, for a long time, been investigating multiagent mobile robot exploration strategies sensitive to communication requirements [2,6]. In this paper, we explore a new behavioral constraint, where a typical scenario involves a team of mobile robots given an exploration task with the requirement that end-to-end line-of-sight communications must be maintained.

Three types of exploration strategies are being studied in this context:

- **Anchored wander**: This is the zeroth level of the exploration strategies. In this scheme no knowledge about the environment is assumed to be available. One member of the team of robots serves as a communications anchor and never moves from its initial position. This anchor is the robot that all robots in the team must maintain a line-of-sight communications channel with. The other robots begin to wander around the environment in sequence. When a breach of the line-of-sight constraint occurs, the robot will retro-traverse, using the previously developed *live-in-past* behavior, in an effort to restore the line-of-sight channel. Once restored, the robot maintains its position while another robot begins wandering through the world.
- **Quadrant-biased anchored wander:** In this strategy, limited low-level world knowledge is incorporated. A team of robots is confronted with a discovery task, e.g., find and report the location of the presence of a biohazard within a building [3]. In our test cases, the environment has been divided into quadrants. The robots only have advance knowledge of which quadrant the target object is likely to be located within. The exploration begins as in anchored wander, but with each robot executing a *biased* wander behavior, gravitating towards the general area where the object is located.
- **Informed Exploration:** With more complete *a priori* knowledge of the environment, informed exploration using path planning strategies becomes possible. With this strategy, the team of robots relies on map knowledge of the interior structure of the building and a tentative location of the target object to disperse themselves along a path in a manner consistent with the maintenance of the line-of-sight communication constraint.

2. Line-of-sight Definitions
A robot *r* is considered to be have a line-of-sight channel to robot *a* if:

1. robot *r* can sense robot *a* directly; or
2. robot *r* can sense a robot *b* directly and robot *b* is considered to have a line-of-sight channel to robot *a*.

In order to implement this definition experimentally, two new perceptual triggers were introduced into the *MissionLab* multiagent mission specification system [5] for establishing the line of sight constraint. They are:

- **Has-Line-Of-Sight-To**. In the context of these missions, robot team members are identified by a unique color. The Has-Line-Of-Sight-To trigger takes as a parameter the color of the robot we are interested in and returns true if the robot

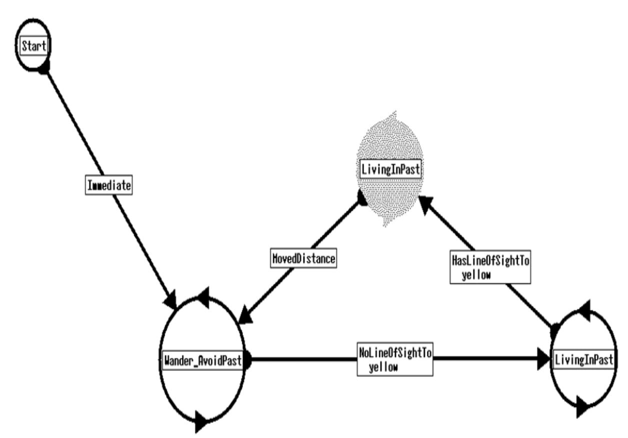

Figure 1. FSA demonstrating the use of the line-of-sight perceptual triggers.

A simple example mission was developed exploiting these line-of-sight triggers. Figure 1 shows the *MissionLab* finite state acceptor (FSA) for that mission. Two behavioral assemblages [1] are involved:

- **Wander-Avoid-Past**. The robot wanders about with a small bias away from areas that it has visited previously. It is composed of the resultant forces of the following motor schemas (behaviors):
    - **Wander**. A behavior that generates a force whose direction is set randomly at intervals of fixed length.
    - **Avoid-Obstacles.** A behavior that generates a force directed away from detected static obstacles.
    - **Avoid-Past**. A behavior that generates a force directed away from previously visited areas.
    - **Probe**. A behavior that generates a force directed towards free space.
- **Living-In-Past**. The robot retro-traverses its path. This assemblage is described in detail in [4]. The pertinent motor schemas are: Avoid-Obstacles, Wander, and Live-In-Past. Live-in-past basically marks in memory areas that the robot has previously occupied and generates repulsive forces away from them.

This first simple mission scenario consists of a team of two robots. One robot remains immobile and acts as an anchor. The second robot executes the Wander-Avoid-Past assemblage until the line-of-sight constraint is broken. The robot will then roughly retrace its steps using the Living-In-Past behavior. Once line-of-sight is restored, the robot continues to revisit its earlier path for a short distance further, and then begins wandering again.
In the next section we build on this simple mission by adding more robots and evaluate the strategy using a notion of coverage.

3. Anchored Wander

Anchored wander is a simple exploration strategy for a team of robots that serves as the baseline for this study. One member of the team of robots serves as the anchor and never moves from its initial position. The anchor is the robot that all robots in the team must maintain a line-of-sight channel with (as formally defined earlier). The anchor robot performs useful work even though it remains immobile after taking up its position at the entry way to a building. It can communicate with the mission operator's home base serving as a relay, providing direct feedback on the overall status of the mission. It may also serve as a sentry, monitoring the area surrounding the entry portal, providing warning to the team should intruders be nearby.

The rest of the team members are involved in active exploration of the environment. In the current implementation, only a single robot is in motion at any one time, serially expanding the explored area. This approach makes it easier to restore the line-of-sight constraint when it becomes violated. It also requires very little communication among the robots regarding their spatial organization. The robots, thus, take turns exploring. During its turn, an active robot will use the Wander-Avoid-Past behavioral assemblage until the line-of-sight constraint is violated, at which point the robot will retro-traverse using the Living-In-Past assemblage. Once the line-of-sight channel is restored, the robot

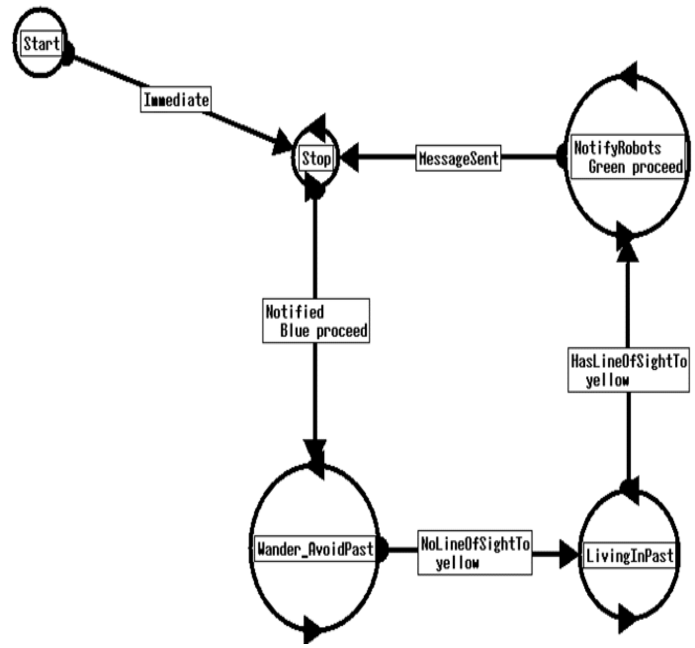

Figure 2: FSA for the coverage task.

To quantitatively investigate the merits of this approach the *coverage* metric was defined. A location in the environment is considered *covered* if at some point in time the location was within the sensor footprint of any robot. With a finite static environment we can then consider coverage as a percentage of the location that has been covered as compared to the total area of the location.

Simulation experiments were conducted to quantify coverage as it relates to time. The first set of experiments was performed in the *Walls* environment (Figure 3). This environment is closed and static. It consists of two hallways and four rooms. In terms of scale, the map is 17 meters wide and 15 meters high. Each simulated robot has a sensor footprint with infinite range (keeping in mind that this only means that the sensor can see only as far as the farthest wall in a room in a building which is a reasonable assumption for this task) and a field-of-view of 45 degrees. The sensor cannot penetrate walls. The mission was run until 95 percent coverage was achieved or 12500 simulation steps had been performed. Each simulation step is considered equivalent to one simulated second of time. Each robot had a simulated movement rate of 0.3 meters per second.

The experiment was repeated forty-nine times and the results averaged, for each of three, four, and five member teams. This data is plotted in figure 4. These results show the approximate expected performance of the robot teams. The three-robot team arrives at 65 percent coverage at the same rate as the other teams, but quickly levels off and reaches an average coverage of 87 percent in these experiments. The performance of the four and five robot teams is even more closely related. Both achieve greater coverage than the three-robot team at 12500 simulation steps, with the five-robot team slightly outperforming the four-robot team. Another useful metric is the percentage of trials in which the robot team exceeded 95 percent coverage. These results are displayed in Table 1. The net outcome is that design guidelines for the necessary number of robots to accomplish this task in a particular environment can be determined, i.e., when there is exhibited a diminishing return on increasing the number of robots. This is similar to performed in earlier work on robot communications that have been reported in greater detail elsewhere [2].

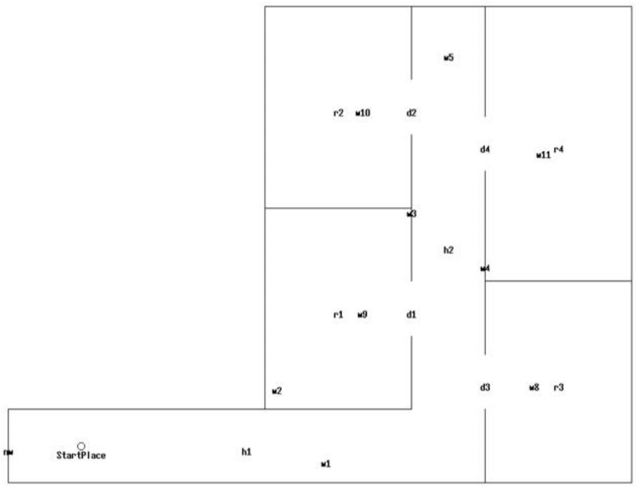

Figure 3: Walls overlay.

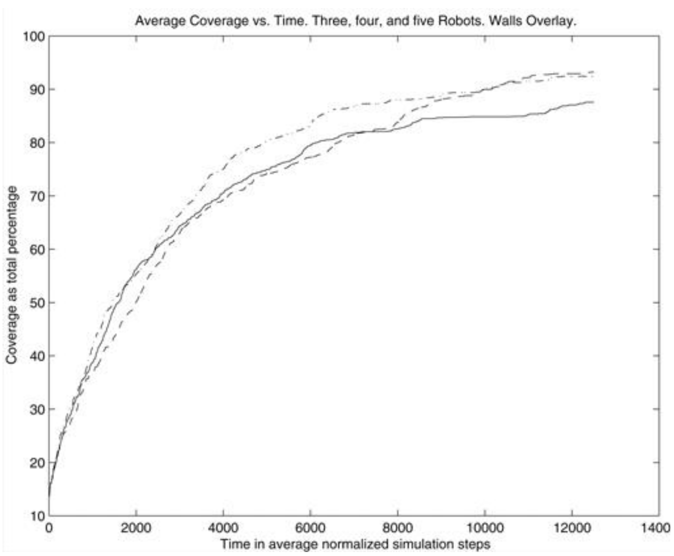

Figure 4: Average coverage over time for three (solid), four (dash-dot), and five (dashed) robots in the Walls environment.

Three robot team	Four robot team	Five robot team
59%	73%	73%

Table 1: Percentage of trials in which the robot team exceeded 95 percent coverage in the Walls environment out of 49 trials each.

Another set of experiments was performed in simulation in a larger and more complicated environment. In these runs, the Manufacturing Research Center (MARC) environment was used (Figure 5). The scale of this map is 45 meters by 45 meters. The conditions for the experiments were the same as before where each simulated robot has a sensor footprint with infinite range and a field-of-view of 45 degrees; the sensor cannot penetrate walls; the mission was run until 95 percent coverage was achieved or 12500 simulation steps had been performed; each simulation step is equivalent to one simulated second of time; and each robot had a simulated movement rate of 0.3 meters per second. The experiment was repeated multiple times for each case and the results averaged, for each of three, four, and five member teams. This data is plotted in figure 6. Forty-nine trials were performed for each of the three and four robot team. Forty trials were performed for the five-robot team.

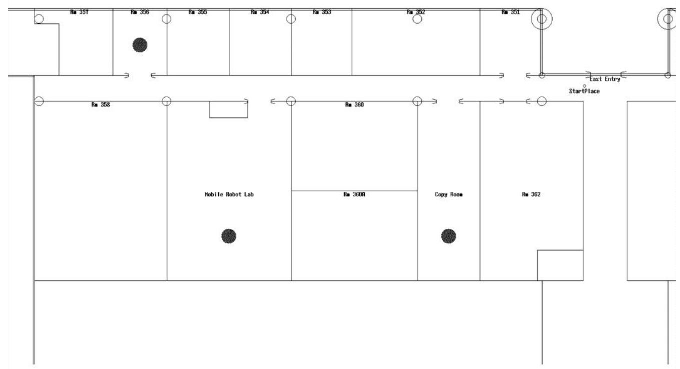

Figure 5: MARC overlay.

These results clearly show slower coverage rates for the MARC environment, as expected, since the area is larger and more complicated. The results would seem to show the robot teams performing similarly. This is likely an artifact of the serial nature of exploration and the structure of this particular environment.

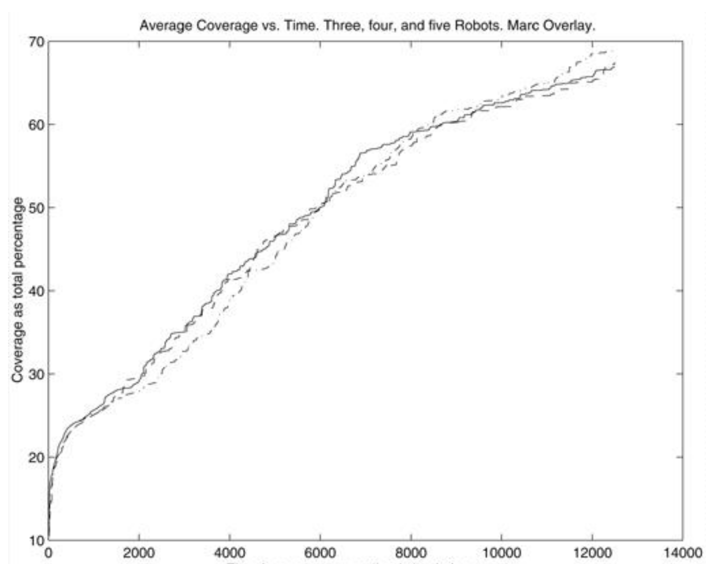

Figure 6: Average coverage over time for three (solid), four (dash-dot), and five (dashed) robots in the MARC environment.

4. Quadrant-biased Anchored Wander

This strategy employs a relatively small amount of world knowledge. The exploration task is now to locate a particular target object as quickly as possible and report back the results, not to maximize coverage. The overall layout of the environment is unknown in advance to the robots. However, the location of the object is known to be within a particular range and extent within the area. For these experiments, the environment is divided into quadrants. The robots are required to locate a single biohazard object that has been placed within one of the four quadrants. The robots are presented with the knowledge in which quadrant the target object lies. This is designed to be similar to the notion of, for example, search in the northwest corner of the building.

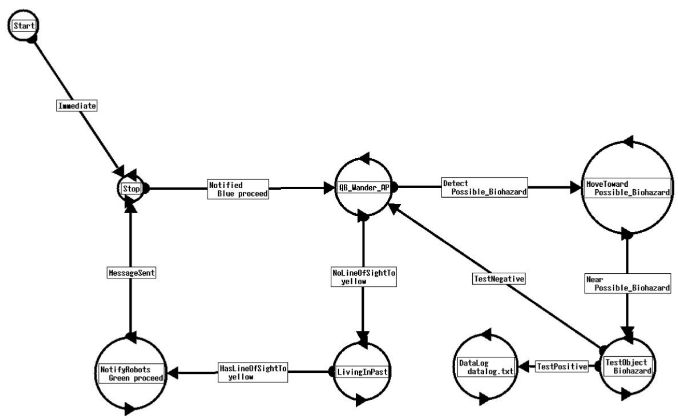

Figure 7: FSA for the discovery task.

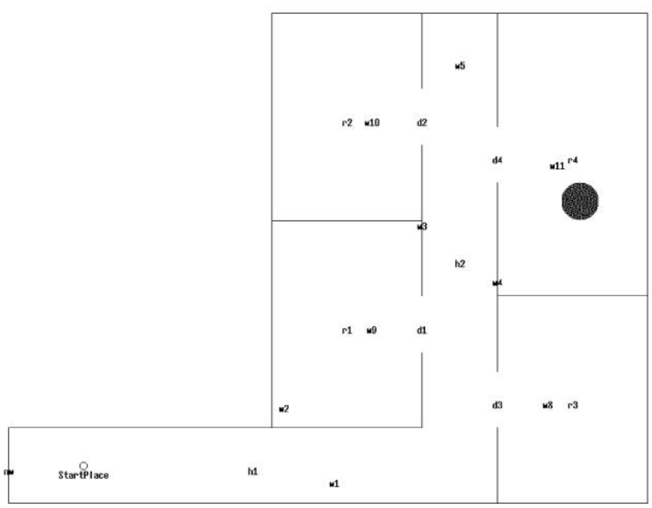

Figure 8: Walls overlay with a biohazard placed in the first quadrant.

In order to harness the quadrant information effectively during the search, a biasing behavior is introduced into the previously mentioned Wander-Avoid-Past assemblage. The biasing force is implemented as a Move-to-Goal motor schema with a small fixed gain. The goal location used by the behavior is chosen randomly as a point within the quadrant where the biohazard is known to be located. Figure 7 depicts the FSA of a single robot performing the discovery task using this method.

A series of simulation runs was conducted to evaluate this method. In these experiments, simulation time until successful discovery of the biohazard by the robot team is measured. In the first set of experiments, a biohazard is placed into the Walls environment within the first quadrant. Figure 8 shows the environmental map. The shaded circle represents the target biohazard. Sixty-three trials for each of three, four, and five member teams were performed. The results are displayed in Figure 9. The mean number of simulation steps required for the discovery task is presented in Table 2.

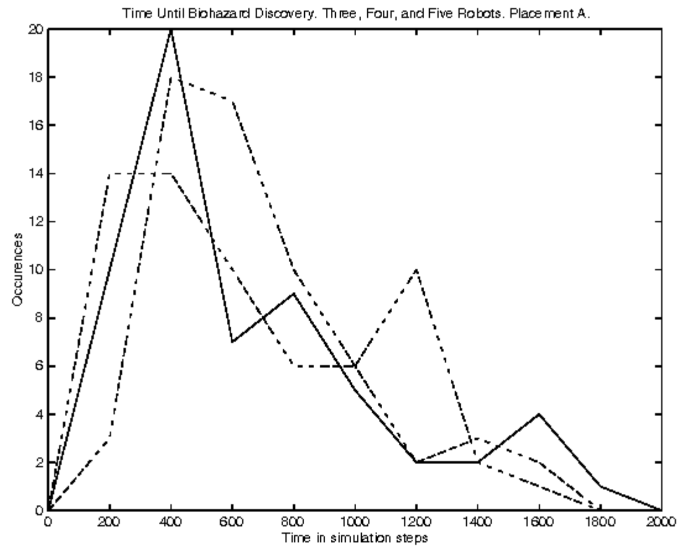

Figure 9: Time until biohazard discovery with three (solid), four (dash-dot), and five (dashed) robots in the Walls environment placement A.

Three robot team	Four robot team	Five robot team
695	602	809

Table 2: Mean number of simulation steps required for biohazard discovery in the Walls environment placement A.

Figure 9 shows that the robot teams tend to perform similarly if the biohazard is located early on during the search. As the number of robots increases, the less heavily tailed the distribution is. This task/environment only requires three robots to be effective as defined. Each robot in the team must begin its exploration from the start place. If the biohazard is found by one of the first three robots, the performance times should be similar for all cases, and any advantage of supplying additional robots is lost (a discovered design criteria). The average simulation steps required for each team are almost identical.

In the second set of experiments, a biohazard is placed into the Walls environment into the third quadrant. Figure 10 shows the map. The shaded circle again represents the biohazard. Twenty-one trials for each of three, four, and five member teams were performed. The results are displayed in Figure 11. The mean number of simulation steps required for the discovery task is presented in Table 3.

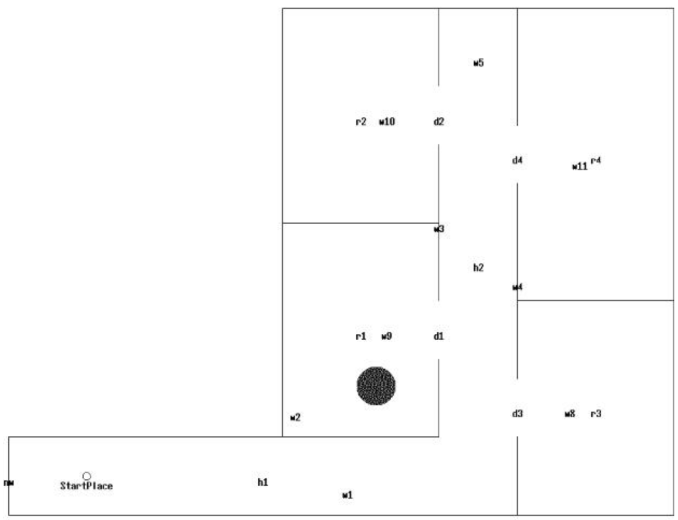

Figure 10: Walls overlay with a biohazard placed in the third quadrant.

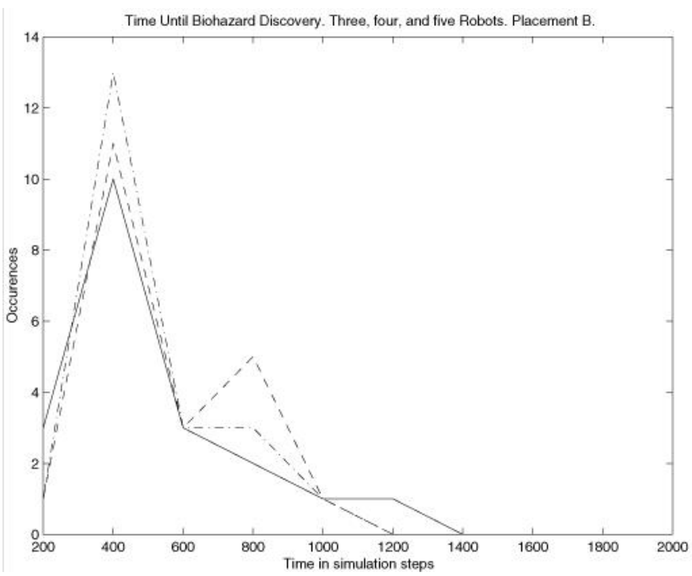

Figure 11:Time until biohazard discovery with three (solid), four (dash-dot), and five (dashed) robots in the Walls environment placement B.

Three robot team	Four robot team	Five robot team
420	390	435

Table 3: Mean number of simulation steps required for biohazard discovery in the Walls environment placement B.

Again, the experiments were repeated in the larger and more complicated MARC environment (Fig. 5). Eighteen trials for each of three, four, and five member teams were performed. The results are displayed in Figure 12. The mean number of simulation steps required for completing the discovery task is presented in Table 4. Comparing the mean discovery times, we note that the four-robot team performs somewhat better than the three-robot team. The five-robot team has the worst mean discovery time. This is due in part to the fact that, with several robots already deployed, a robot freshly receiving its turn to navigate can wander over a large area without breaking the line-of-sight constraint, repeating the work of previous robots.

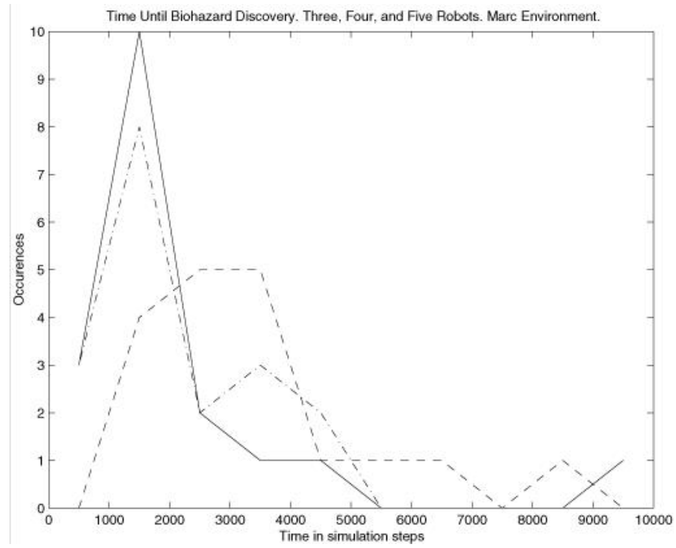

Figure 12: Time until biohazard discovery with three (solid), four (dash-dot), and five (dashed) robots in the MARC environment.

Three robot team	Four robot team	Five robot team
2234	2085	3345

Table 4: Mean number of simulation steps required for biohazard discovery in the MARC environment.

5. Informed Exploration

With more complete *a priori* knowledge of the environment available, more informed strategies for navigation become possible. In the case of informed exploration, the team of robots relies on map knowledge of the interior structure of the building to produce a pathway to the suspected target. They are provided with a tentative location of the target object. The team then needs to disperse themselves along the computed path from their starting place to the target in a manner consistent with the maintenance of the line-of-sight communication constraint. In this set of experiments, the system is in possession of a detailed map of the environment. Given the map, it is possible to determine ahead of time the path the robots should follow to acquire a known target, so the task evolves into one of distribution along this path in a manner that will preserve communications. Recognizing that the world model is not always accurate and that unmodeled obstacles may be present it is still important to use behavioral methods, as a purely theoretical analysis of the environment done in advance will likely be inadequate.

Two methods are examined for creating the route to be followed. In the first, the operator, using the MissionLab waypoint creation tool, lays the route out manually. Using the tool, the user places a series of waypoints by clicking the mouse on the map. This directly generates the route that the robots will follow. Using the second method, the route is generated from an automated path planner [7]. The path planner requires minor interaction with the user. When the path-planning tool is launched, the environmental map is displayed and the user is asked to click on the desired target location. The path planner then automatically generates a series of waypoints for the robot team to follow. Each waypoint in the route is implemented as a *GoTo* assemblage, which is composed of the Avoid-Obstacles and Move-to-Goal motor schemas among others.

In either case, the method the robot team uses to traverse the waypoints is similar to that of the informed exploration strategy but uses the waypoints as intermediate goals. Again there will be one robot anchor that does not move from the start position. Each robot will in turn attempt to traverse the entire series of waypoints, one after the other. If at any point the robot moves in a manner that violates the line-of-sight constraint, the robot uses the Living-in-Past assemblage to retro-traverse until the line-of-sight communications channel is restored. Figure 13 depicts the FSA for a single robot following a typical route created by the path planner.

Several experiments were performed on the Walls environment with biohazard placement A (Figure 8). In each experiment a team of four robots was used. In one set of experiments the route was generated by the path planner. In the second set the route was generated by hand. Each set of experiments was repeated twenty-one times. Table 5 gives the mean number of simulation steps and standard deviation for each approach. The route created by the path planner takes slightly longer since it placed its first waypoint at the very start of the hallway. The number of simulation steps taken by each route is at least twice as fast as the four-robot team took to discover the biohazard using only the quadrant-biased wander technique. Also note the small standard deviation. Obviously using available knowledge, when reliable and stable, is a useful thing to do.

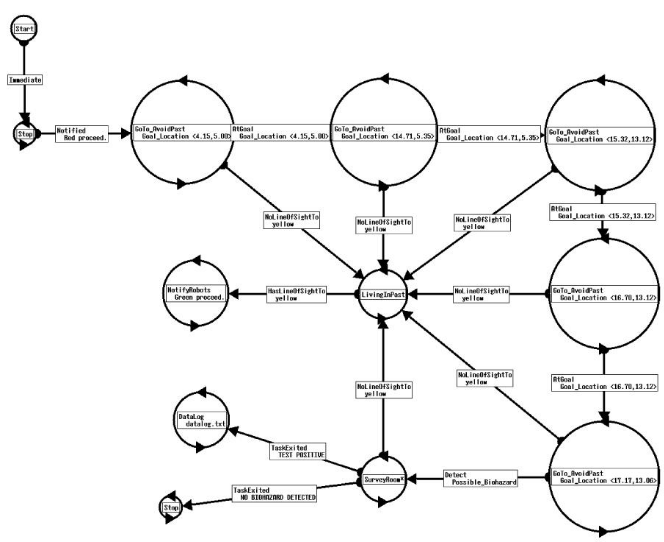

Figure 13: FSA for the discovery task using path planning.

Path planner mean simulation steps	STD	Hand created mean simulation steps	STD
363	7	247	20

Table 5: Mean simulation steps till discovery in the Walls environment, using precomputed routes.

6. CONCLUSIONS

We presented several local navigation strategies for a team of robots capable of working with varying degrees of *a priori* knowledge: from none to a complete world map. For each of these strategies, every robot team member is required to maintain a line-of-sight communications channel with the anchor robot. The most basic of the navigation strategies is the anchored wander. Without any environmental information available, wandering is useful and productive. It relies on nondeterminism to guide the robots to unexplored locations, while avoiding areas previously visited. In the Walls simulation test environment, the anchored wander strategy reaches 95% coverage quite regularly. When the anchored wander strategy is used to explore the more complex MARC environment, it does not perform as well. It is expected that as the complexity and size of the environment grows, a strategy based purely on wandering becomes less effective.

Two more navigation strategies were presented that are of use when an increasing level of *a priori* information is available. The first was the quadrant-biased anchored wander. A small directional bias encourages the robot to wander towards the desired area to explore in search of a target object. A gain in information available produces a similar gain in discovery time. The strategy still relies heavily on nondeterminism, (to a lesser degree than before) to guide the robot to its target. Varying the strength of the biasing force was not explored.

The last strategy presented was route following. This strategy requires strong prior knowledge of the layout of the environment. It shows that more effective solutions exist when more reliable information about the task environment is available. With a detailed map the robots are able to navigate quickly to the desired target. The results of path planning are more consistent as well, as demonstrated by the small standard deviation.

7. ACKNOWLEDGMENTS

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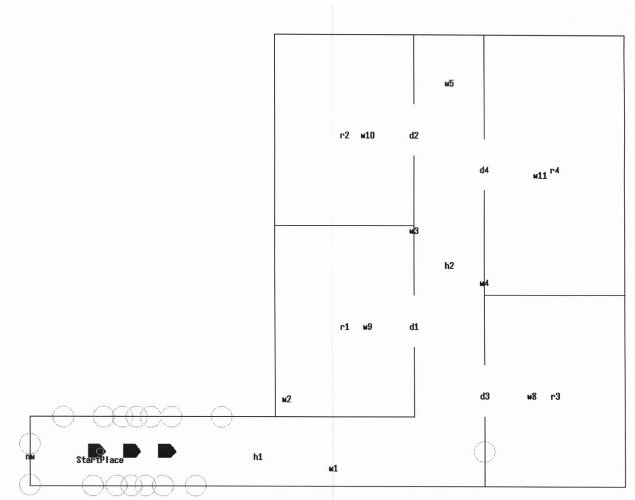
Appendix: Example Coverage Mission

This appendix presents a sequence of figures illustrating how the robots accomplish a coverage mission as described in Section 3 of this paper.

1.) Three robots begin at the start place.
2) The second robot begins exploring until the line-of-sight constraint is broken. This occurs at the hallway junction.
3) The third robot is then able to explore until its line-of-sight constraint is violated. This occurs in the lower left-hand room.
4) The third robot then continues to explore other rooms.
5) The robots will continue to take turns exploring. Typically some oscillatory behavior will occur when the communications channel is violated, until useful exploration can take place with the line-of-sight channel unbroken.



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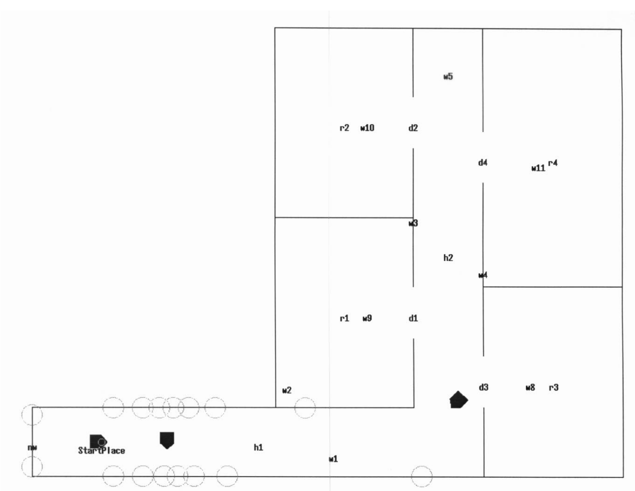

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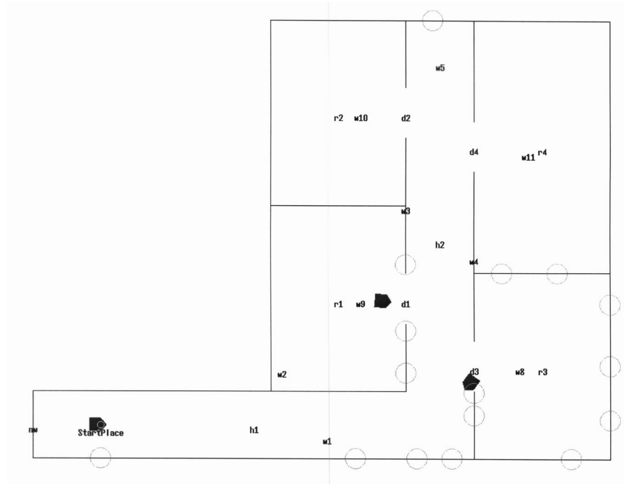

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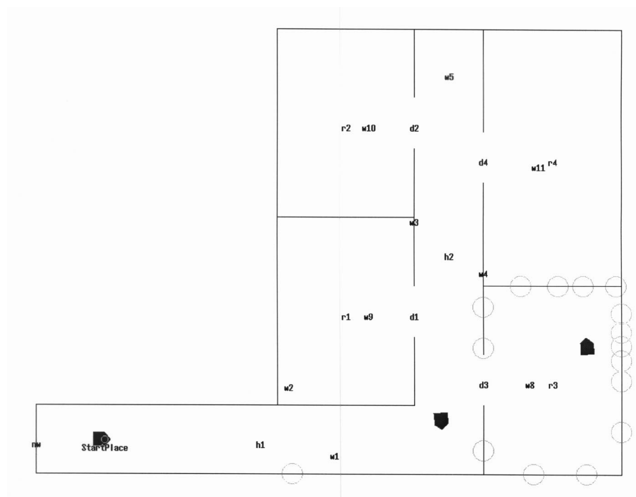

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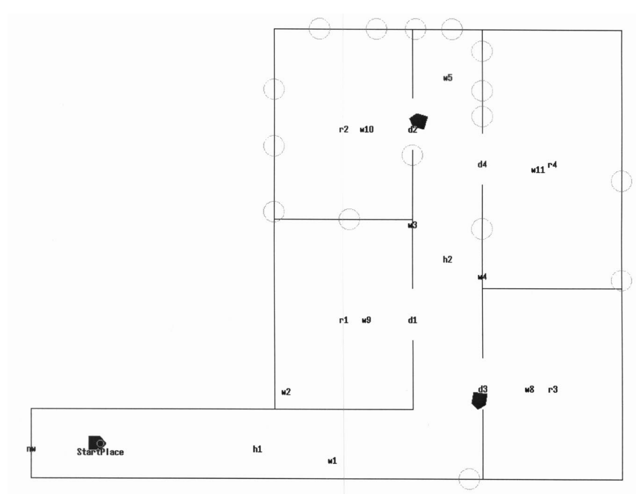

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