A Hybrid Evolutionary Probablistic Framework for Developing Robotic Team Behaviors

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Abstract. One of the inherent issues in team-based multiagent robotics is coordinating a cooperative task decomposition. Use of explicit communication models or game theoretic approaches to model teammate behaviors can be costly and error-prone. This paper describes a method of discovering a set of behaviors that allows a team to intrisically function in a collaborative manner. Probabilistic planners based on spreading activation networks that determine these behaviors are implemented in each robot. A genetic algorithm is used to find the appropriate link strengths within each of these networks to produce an overall dynamic team. It is shown that a team controlled by spreading activation networks can perform well as a team by maintaining these behaviors in environmental situations other than the one used for GA evolution. From this framework, a goal-directed task planning approach can be envisioned to deploy a fully functional robot team.

1 Introduction

Many applications in robotics focus on the design of a single agent capable of solving a complex problem. However, certain domains may be better suited for a team of robots. There are several reasons common to various scenarios in which multiple robots may be better than one [1]. Multiple robots are capable of being in several places at the same time and can perform distributed action in parallel. A team can coordinate the decomposition of a problem by effectively breaking it down into multiple subproblems. In a task like exploration or foraging, multiple robots can learn the environment and explore more of it in less time than a single robot. Finally, multiple robots can be designed to be less complex than a single robot given the same task.

One way of producing a cooperative relationship between team members is by assigning a specific goal to each member. This method likely requires an explicit decomposition of the task the agents are collaborating upon. In some tasks, a team of robots may not be capable of explicitly communicating this decomposition with one another, either because of communication issues or due to the complexity of the problem including robot interference.

It is desirable to show that if each team member instead exhibits a certain behavior conducive to solving a certain part of a problem, and the entire team consists of behaviors that mutually complement each other, then the agents can collectively solve the problem without being assigned explicit subgoals.

This paper focuses on designing a framework to develop the behaviors of individual robots that comprise the team by developing a Bayesian network within each robot that captures the correlation between actions of the robot and the observed state of the environment. These behaviors are generated through a probabilistic planner within each robot. The probabilistic planner is implemented as a spreading activation network over the Bayesian network, such that condition-action-effect success likelihoods are based on what is known about the current state of the environment. Each planner will have different link strengths between an action and its relation to an environmental condition, and the goal is to develop the link strengths of each planner so as to produce an overall desirable team behavior.

In order to demonstrate this conceptual framework, an experimental simulation test-bed is built comprising several robots dispersed in a field containing a certain number of light sources. The goal is to locate as many light sources as a possible within a pre-specified amount of time. This specific task is better suited for a team of robots since the area to be covered can be divided and explored more quickly by the whole team. The problem of effectively coordinating team behavior involves subproblems such as minimizing robot interference and overlap of work between robots.

A fundamental issue then arises: how are the link strengths of the spreading activation network determined for each robot? The large search space of potential link values for each robot, and for the team as a whole, makes it prohibitive from a computational standpoint to perform an exhaustive search. Therefore, a search based on genetic algorithms (GA) is employed. The GA searches for collective action sequences to produce collective team behaviors that maximize exploration and localization of light sources. From the evolved team, condition-action vectors experienced during simulation are recorded and used to seed the link strengths between actions and possible effects within the spreading activation networks. Each team member should experience a different section of the environment for effective decomposition of the task at hand, and the corresponding condition-action vectors are then captured to yield the desired team behavior.

2 Background Work

The majority of the spreading activation task planner design is based on a probabilistic planner developed by a team at Vanderbilt University [2]. A layered control architecture is designed based on work related to the DAC5 control system [3] used in a similar foraging task. Many design choices were made when developing this particular multi-agent system, each with their own tradeoffs [4]. A few of these tradeoffs are identified and examined next.

2.1 Team Learning Versus Concurrent Learning

In some cases, team learning refers to an implementation that involves a single, central learner. On the other hand, in concurrent learning, learning occurs in each robot. In this case, learning is distributed as tends to be the case in many real environments where learning takes place online; i.e., while the robots are operating. This case enables robots to learn separate tasks or subtasks.

In this work, a GA is used where genes comprise the action sequence used by each robot during simulation. The performance of each robot is evaluated by the fitness function. The population of genes is broken down so that a separate subpopulation of genes is dedicated to evolve the action sequence for a given robot.

2.2 Evolving a Team to Solve a Common Problem

Using an evolutionary technique, such as GAs, depends on defining a fitness function. The task of evolving robots for exploration as opposed to locating an item is primarily specified in the GA through the fitness function. Once a framework is set up for multiple agents to learn a specific task, the desired performance can be altered to another task by changing the fitness function. Given a common fitness function with the proper constraints, a GA will search for a team that naturally decomposes a problem into subproblems.

3 Forming Effective Teams: A Hybrid Approach

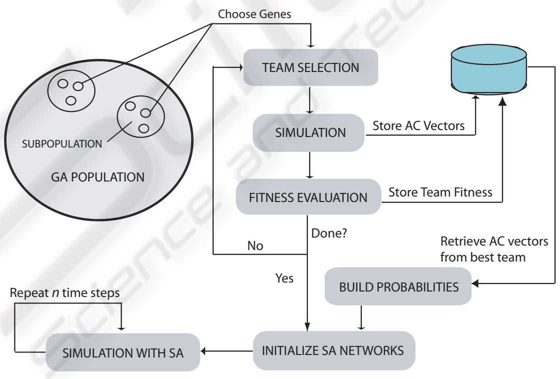


Fig. 1. Block diagram of the hybrid approach.

Figure 1 outlines the major steps of the framework designed in this work. Initially, a genetic algorithm is used to search for collective action sequences that maximize team performance. This involves repeating the steps of team selection, simulation, and fitness evaluation until an appropriate team is identified. The action-condition vectors and team fitness values are stored for each generation, and following evolution, the vectors which represent the best evolved team are used to build probabilities (represented by link strengths) within each spreading activation network.

These link strengths distinguish behaviors among the robots as all other aspects of the spreading activation networks are identical between robots, along with designer-specified goals. Once the spreading activation networks are initialized, each robot is controlled through a reactive and adaptive layered approach.

3.1 Employing a Genetic Algorithm

Producing good overall team performance depends on determining the link weights of the spreading activation network for each robot. Given the large search space for potential values, a GA was chosen as the search mechanism. Although a GA could be used directly to find these link strengths, the approach taken is to use the GA to evolve the action sequences of the team. Searching for action sequences is likely a more direct and time efficient search since the genes of the GA consist only of n possible actions. The link strengths are encoded in the genotypes of the GA using real values ranging between [-1 and 1]. Therefore, with a small and static set of possible values for each allele, convergence times could be drastically reduced. To further reduce the search complexity, genes are divided into subpopulations, with each subpopulation maintained for a separate robot.

3.2 Using GA Subpopulations

In general, by partioning a population of genes into subpopulations, a variety of new possibilities emerge. If each individual of a subpopulation is only mated with another member of the same subpopulation, then the structures between subpopulations can vary. This gives rise to different species of genes and allows for a simple way to keep track of which individuals can pair with which others during crossover. Other methods of maintaining species include assigning an innovation number [5], which would allow for multiple species to coexist within a subpopulation. Subpopulations are mainly used in this experiment to allow each robot to develop a different behavior and to allow the decomposition of the problem. Each robot is assigned a specific subpopulation throughout the evolution process. In this way, the subpopulations for each robot may converge towards different subgoals, resulting in the desired implicit task decomposition. Within each subpopulation, individuals are assigned fitness values based on performance during simulations. Additionally, a team fitness value is maintained for every group of individuals used together in each simulation run. This team fitness value is used to produce cooperative behavior: a combination of individuals that perform well together by exhibiting task decomposition is given a higher team fitness value.

3.3 Spreading Activation Networks

A spreading activation network as used in this work is a connectionist type network in which layers of nodes represent either possible actions or possible states of the environment as perceived via the robot sensors. Spreading activation is attractive because it allows for efficient search potentially in parallel and in a fashion that happens to be analogous to human information processing [6].

The behaviors of team members are determined by the weights of links that connect layers of the spreading activation networks. Figure 4 shows a portion of a spreading activation network such as those used in the experiments. The weights between preconditions (the value of conditions observable in the current state of the environment) and actions, as well as between actions and post-conditions (in the next state) can be defined differently for each member of the team. These weights determine how each robot will make decisions: if the resulting probability of a certain action sequence being successful in bringing a robot to a goal condition is higher for one robot, it may perform this sequence where another robot in the same state would not.

3.4 Probabilistic Task Planning

Goal-oriented planning techniques are utilized that involve back propagation of goal utilities, forward propagation of condition utilities, and action selection as previously developed in [2]. In particular, when the adaptive control layer is active (indicating no direct rewards), planning is performed until one of the actions in the current state accumulates enough utility and is selected. Action utilities are typically compared to a threshold value, and when an action exceeds this threshold, it is selected.

Figure 4 shows a portion of the spreading activation network. The first layer consists of conditions observed in the environment, or the preconditions present before acting. These preconditions are linked to possible actions the robot may perform, and the connections indicate the likelihood of an action succeeding given the state. These links, denoted w_{ij}, are determined by the following equations [2]:

$$w_{ij} = \begin{cases} > 0 & \text{if } (c_i = \text{T}) \text{ increases P}(a_j^{success}) \\ < 0 & \text{if } (c_i = \text{T}) \text{ decreases P}(a_j^{success}) \end{cases} \tag{1}$$

where T indicates a true condition and F a false condition. The link strength w_{jk} between an action a_j and one of its effect propositions c_k is defined as follows:

$$w_{jk} = \begin{cases} P(c_k = \text{T}|a_j^{exec}) & \text{if } a_j \text{ sets } (c_k = \text{T}) \\ -P(c_k = \text{F}|a_j^{exec}) & \text{if } a_j \text{ sets } (c_k = \text{F}) \end{cases} \tag{2}$$

During backpropagation, action utilities are then updated to determine the best action to take. First goal utilities $U(c_k)$ are examined:

$$U(c_k) = \begin{cases} > 0 & \text{if } (c_k = \text{T}) \in \textbf{G} \\ < 0 & \text{if } (c_k = \text{F}) \in \textbf{G} \\ = 0 & \text{if } c_k \notin \textbf{G} \end{cases} \tag{3}$$

Then the utility of condition c_k is combined with the probability of the condition existing in the current state of the environment and action-effect link strengths to determine the reward of performing an action a_j:

$$R(a_j|c_k) = \begin{cases} w_{jk}P(c_k = \text{F}|S_t)U(c_k) & \text{if}(w_{jk} > 0) \\ w_{jk}P(c_k = \text{T}|S_t)U(c_k) & \text{if}(w_{jk} < 0) \end{cases} \tag{4}$$

These action rewards are summed over all conditions defining the action utility for action a_j:

$$U(a_j|S_t) = -C(a_j) + \sum_k P(a_j^{success}|S_t)R(a_j|c_k) \tag{5}$$

3.5 Extracting Action-Condition Vectors

The action sequences that represent the best team are extracted from the GA and paired with the condition vectors recorded during the simulation of that team. For every action in the sequence, the condition vector contains the corresponding environmental conditions present. The link strengths between actions and effects of the spreading activation networks are seeded with these action-condition pairs by evaluating the distribution of conditions that occured after every action. A link strength w_{jk} is then determined by the frequency of an effect proposition being true after an action was executed over n simulation steps:

$$w_{jk} = \frac{1}{n} \sum_n \begin{cases} +1 & \text{if } (c_k = \text{true}|a_j^{exec}) \\ -1 & \text{if } (c_k = \text{false}|a_j^{exec}) \end{cases} \tag{6}$$

Frequency is incremented for every condition c_k that is true after action a_j is executed. If c_k is false after action a_j is executed, the frenquency count is decremented. This method effectively correlates actions with effects as they tend to appear in the observed environment. If an action a_j results in equally frequent occurrences of c_k being true and false, w_{jk} will accumulate to zero, indicating no relationship.

3.6 Switching Between Reactive Control and Planning

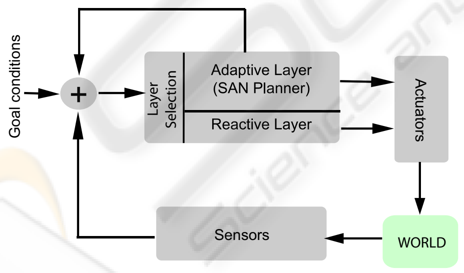


Fig. 2. Block diagram of the control system. The reactive layer is activated whenever the sensors return values that pass a threshold and indicate a goal condition.

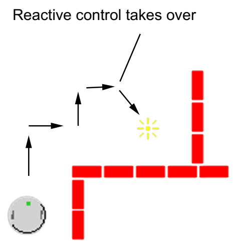


Fig. 3. A scenario demonstrating a switch between adaptive and reactive control.

To improve individual performance, a distributed control model was then developed which incorporates a two-layered approach: a reactive control layer is used in situations where a sensor stimuli indicates a direct reward (either positive or negative), and an adaptive control layer is used where no direct reward is observable from the sensors thus requiring planning (see Figure 2). The reactive control layer equips the robot with minimal behavioral competence to deal with its environment and is only active when a target (light source) or collision condition are certain to occur if the robot does not react. Figure 3 shows an example of a robot that is exploring towards the north-east while a wall is sensed on the right. Also shown is how the reactive control layer takes over as soon as a direct reward is observable (here the light sensors have discovered a light source and the robot turns towards it). The amount of planning at any time during execution varies depending on how many action-condition steps need to be evaluated to achieve a high enough action utility for an action at the current step, which is discussed further in section 4.

4 Implementation

A Khepera robot simulator is used in this work as described below. The task given is to localize as many light sources as possible in a prespecified amount of time, which should be solved best by a team that works together by dividing up the map between robots to cover the largest possible area. Initially, action sequences are evolved to find an optimal team as defined by the set of action sequences. Then, control is transferred to spreading activation networks and performance is qualitatively evaluated.

Three types of sensors are incorporated into the conditions layer of the spreading activation network: 8 light sensors, 8 distance sensors, and a compass. Each of these types is divided so as to produce four Boolean conditions for each type. For the light and distance sensors, threshold values are used to specify whether a wall (light) is detected directly in front, to the left, to the right, or behind the robot. The compass is used to record roughly which of the eight cardinal directions the robot is facing. Figure 4 indicates these conditions in the preconditions and effects layers of the network.

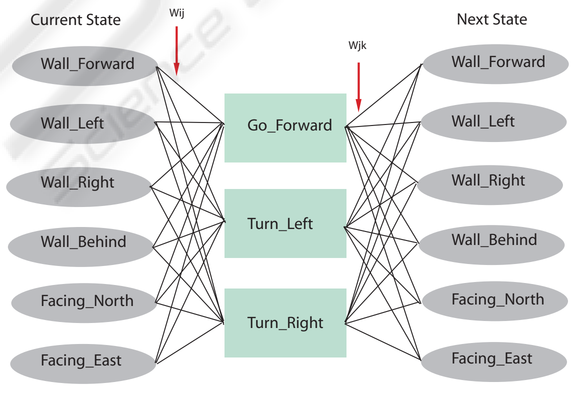


Fig. 4. Portion of the spreading activation network.

The actions a robot may perform are limited to forward movement, turning left, or turning right. An *action period* is defined so that the robot does not attempt to plan at each time step (since very little would have changed in the environment). Between each action period, the robot examines its current state received from the sensors, and if no direct reward is in the state it will plan. Once a decision is made, an action is performed for *action period* time steps, and the sensors are examined for direct rewards and otherwise planning begins again. This allows the robot to choose the optimal decision based on known probabilities at each action period.

4.1 Simulator

The experiment makes use of a freely available Khepera simulator written in C [7]. The simulator evolved into a higher level and more general program called Webots (not a freeware) that allows for more sophisticated simulations on a number of robots and platforms.

An alternative Khepera simulator, KiKS [8], was also considered. KiKS is Matlab-based and provides a smoother interface and multiple robot support via a network client/server implementation. However, for the purpose of implementing GAs, this simulator may be less suitable. The fastest simulation run of a single robot that was achieved with visualization turned off was 2000% the speed of the Khepera being simulated, with a simulation of 200 steps taking a matter of seconds. Since a typical GA evolution can involve thousands of simulation runs, this severely impacts the degree to which the networks could be feasibly evolved. Additionally, since multi robot support is currently network-based, evolution of multiple robots seems even less suited to this simulator. The lightweight C simulator can be run orders of magnitude faster than KiKS, and this ultimately led to selecting it as the simulator for the experiments we conducted.

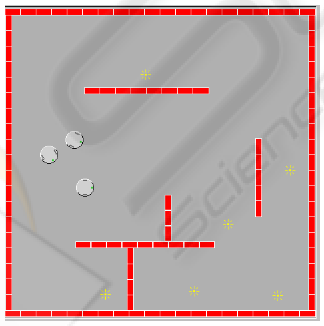


Fig. 5. The C-based Khepera simulator and environment used. The team of three robots begin in the lefthand section of the map.

Table 1. Parameters for genetic algorithm

Parameter	Value
Gene size (action sequence length)	140
Subpopulation size	7
Number of subpopulations	3
Max generations	30
Elitist genes per generation	1
Crossover rate	0.9
Mutation rate	0.05

4.2 The Evolutionary Process

The GA was implemented with parameters as shown in Table 1. One subpopulation is assigned permanently to each robot, which consists of 7 action sequence genes. Initially, all gene alleles are assigned one of three action values: FORWARD, TURN_LEFT, and TURN_RIGHT are the possibilities with FORWARD being 80% as likely as the other two. At each stage of evolution the genes are evaluated, and the gene with the highest fitness value is flagged as the 'best' of the subpopulation. These best genes are copied directly to the next generation. This method of elitism ensures that individuals with very high fitness are not lost through further evolution. The rest of the genes are then sequentially processed. For each gene, there is a 5% chance of mutation, and if mutation takes place then 5% of the gene is assigned a random action. If the gene is not mutated, then it undergoes crossover with a random individual from the subpopulation. Crossover takes place uniformly at one random point where the action sequence values are swapped between the two individuals.

4.3 Evaluating Fitness

The map on which the experiment took place has dimensions 1000.0 by 1000.0 and is shown in Figure 5. The map was partioned into 100x100 equal sized sections. During a simulated run, the path of each robot is tracked, and the number of sections traversed is tallied. Along with this exploration fitness, the number of light sources each robot encounters is recorded. The fitness function assigned to each action sequence gene is as follows:

$$F_i = s_i + (500l_i) \tag{7}$$

$$F(n) = \sum_{i \in n} (F_i + 100l_i) \tag{8}$$

where in (7), s_i indicates the number of unique sections of the map member i explored and l_i refers to the number of different light sources discovered with this action sequence. The fitness function assesses a combination of the team and individual fitnesses. A majority of weight is placed on individual fitness, but members are also rewarded for working well with others: the team members in the combination set n in (8) the fitness values from (7) are summed, and extra reward is assigned for the number of light sources the entire team discovered. Figure 6 shows the typical performance results of the GA in a plot of best team fitnesses achieved over 30 generations. Figure 7 shows the average fitnesses of each subpopulation along with the fitnesses of the best members.

A typical resulting best team performance simulation is shown in Figure 8. In this simulation, each of the three robots explores a separate major section of the map. Each of the three robots begins in the same initial position each simulation run with all three robots in the center of the board side by side. Every member of every subpopulation is run against every member of every other subpopulation. This increases the search space significantly, which is one of the reasons a smal subpopulation size and only three robots were used. At the end of each run, the genes are assigned individual fitness values and the team of genes is given a team fitness value.

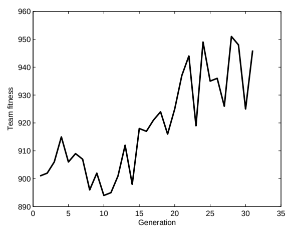


Fig. 6. Best team fitness values over generations.

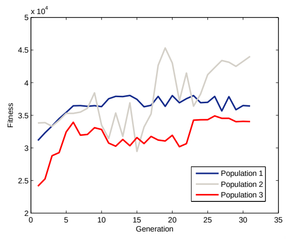


Fig. 7. Individual Fitness values of best members of each generation.

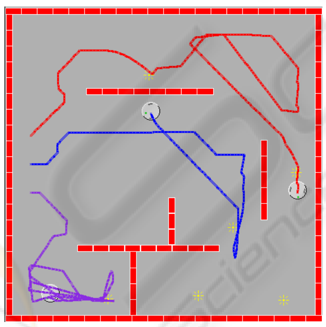


Fig. 8. Paths of an evolved team. Each member of the team explores a separate section of the map.

Table 2. Rewards for Environmental Goal Conditions

Goal Condition	Reward Value
Wall in front of robot	-10
Wall left of robot	5
Wall right of robot	5
Wall behind robot	10
Light in front of robot	30
Light left of robot	20
Light right of robot	20
Light behind robot	20

4.4 Simulating Team Behaviors

The spreading activation networks are then initialized. Each network consists of three layers. The preconditions layer is initialized with propositions as observed in the current state of the environment. The effect (or postconditional) layer consists of reward values for each condition being present in the goal state, which then determine action utility as in (3). Table 2 shows the reward values assigned to each condition. A negative reward implies that the condition is undesirable, which is the case with a wall in front of the robot. With negative rewards, the robot will plan against adverse environmental conditions: for instance, if it is likely that a wall will be observable in front of the robot after performing an action, that action's utility is lessened. Also, by assigning positive rewards to having a wall on the left or right of the robot (as is the case in Table 2) will result in a wall following behavior.

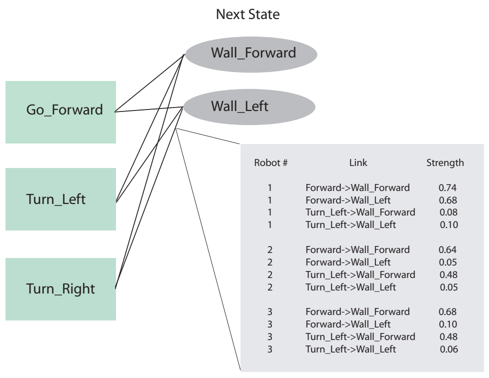
Table 2 does not include rewards given for each specific orientation. Assigning a higher reward to facing north and east, for instance, would result in robots that tend to explore towards the northeast. However, since these rewards are common to all robots, it is undesirable to hardcode behaviors in this way. Instead, the link strengths between these orientation conditions and each action, which are unique for each robot, will provide these behaviors. These orientation reward values must be balanced with other utilities, such as wall conditions, otherwise the robot may prefer to face a wall as long as it is oriented in the preferred direction. Also, these orientation rewards should not be hardcoded to zero, or robots will be unable to develop behaviors based on these conditions.

In selecting actions there is often the possibility that no action seems desirable, or all actions seem equally desirable. In these situations the robot may continue planning indefinitely. To keep this from occuring, the forward propagation lookahead is limited to a value assigned at design time. The value chosen for the experiments was 4 lookahead states. In the case that no conditions are present in the environment to make any of the possible actions desirable (i.e. all action utilities are zero), the default action is to move forward. This is rarely needed when the orientation conditions can themselves cause an action to be desirable, which is further discussed in the next section.

4.5 Applying Evolved Team Actions to Spreading Activation

Next, the action sequences and corresponding condition vectors of the best team simulation run from the GA evolution are used to initialize the link strengths of the spreading activation networks. A portion of these link strengths are shown in Figure 9. Since these link strengths are limited directly to the experience of the particular run corresponding to the GA simulation, they are heavily biased to that particular run and are not guaranteed to necessarily represent the environment accurately. However, the biasing results in each robot exhibiting a different behavior based on how they perceive the environment. It is through this biasing that behaviors are developed.

Figure 10 shows a resulting simulation of 2000 time steps, or equivalently twice the length of action sequences used in the GA simulations. Heterogeneous robot behaviors are apparent from the figure. The path of robot #2, indicated in blue, is the least productive, but exhibits wall-following around the perimeter of the map. Robot 1, with a path



Robot #	Link	Strength
1	Forward->Wall_Forward	0.74
1	Forward->Wall_Left	0.68
1	Turn_Left->Wall_Forward	0.08
1	Turn_Left->Wall_Left	0.10
2	Forward->Wall_Forward	0.64
2	Forward->Wall_Left	0.05
2	Turn_Left->Wall_Forward	0.48
2	Turn_Left->Wall_Left	0.05
3	Forward->Wall_Forward	0.68
3	Forward->Wall_Left	0.10
3	Turn_Left->Wall_Forward	0.48
3	Turn_Left->Wall_Left	0.06

Fig. 9. A portion of the link strengths in resulting spreading activation networks. Link strengths for turning left if there is a wall forward vary: Robot 1 would turn left and Robot 2 would turn right.

indicated in red, discovers the most light sources by exhibiting a wall-adverse behavior. The third robot, path indicated in purple, makes its way into the corner but becomes trapped near that light source.

In Figure 10 it also indicated at what points the robots are being controlled by the spreading activation networks (*adaptive control*) and when they are being controlled by the *reactive control* layer. When a light source becomes observable by the sensors, the robot reflexively turns towards it. If the IR distance sensors detect a wall in front-left or front-right of the robot, the robot will turn reflexively in the direction opposite to the wall to avoid a collision.

Figure 11 demonstrates a second simulation result. This time the robots were started in a different area of the map than where they were trained through the GA simulations. The results are consistent with those as shown in 10: Robot 2 (blue) exhibits wall-following, robot 1 (red) exhibits wall-adverseness, and robot 3 (purple) stays around light sources. The consistency of behaviors confirm that the spreading activation networks are controlling the actions of the robots for the majority of the time.

5 Discussion

The results from the simulation indicate that behaviors can be successfully defined by link strengths within spreading activation networks, and this is a successful framework for developing such behaviors. These behaviors are more robust than the action sequences evolved by the GA, since the robots can be initialized in different areas (or different maps) and their performance will remain about the same.

It should be noted that the robots did not perform as well as teams when controlled by the spreading activation networks as compared to the evolved GA sequences, but some task decomposition was still present. By exhibiting different behavioral roles, like wall-following versus wall-adverseness, a team of mobile robots is able to explore

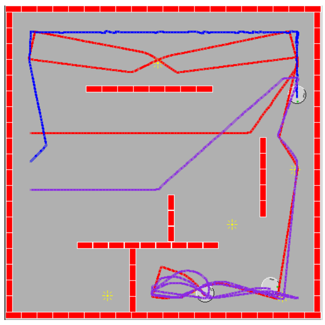


Fig. 10. Paths achieved in the same environment by a team controlled by spreading activation networks and reactive control.

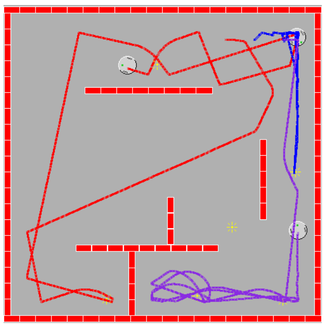


Fig. 11. Paths achieved by starting the robots in another part of the environment using the same network link strengths.

more features of any environment. This environmental independence is probably the most useful result of this experiment.

Reactive control was introduced into the framework design for the purposes of speeding up GA evolution. Without reactive control, the action sequences produced would often result in robots running against walls for time segments and hindered overall progress. Reactive control, however, adds a bit of additional uncertainty into the design of action sequences. Robots may be reacting to a wall or to another robot in the same way. This is ultimately a sensory issue and remains to be addressed.

The GA succeeded in this experiment in decomposing the task of maximizing exploration between members of the team. Since the problem of optimizing cooperative team search behavior appears to be NP-hard, it was well suited for a GA search. By tweaking the actual fitness functions (7) and (8) this decomposition could be manipulated. After most evolutions achieved during the simulations, there was one robot which evolved better than the others. This robot may have in a way hindered the evolution of other robots when team fitness was evaluated. Since this action sequence achieved a high fitness value, it was not as imperative that the other action sequences present in this particular simulation be as fit in order to survive. By adjusting the team and individual fitness functions appropriately, convergence of best team fitness values should be possible.

The idea behind mapping the action-condition vectors to link strengths of spreading activation networks can be compared to other behavior-based techniques. It is believed that defining these link strengths based on the performance of only one simulation may not have provided adequate information for creating a robust decision-making framework. One way of remedying this problem is to increase the length of the action sequences that make up the GA genes but with the cost of greater computation time in performing evolution. Another way would be to evolve the genes until each subpopulation converges to almost the same action sequences. Then, using all of the genes from each subpopulation in creating link strengths of the spreading activation networks would provide more of an aggregated representation of the appropriate action sequences.

The framework developed to this point only addresses the first portion of what would be required to deploy a team of goal-directed robots. The latter portion requires supplementing this framework with a full, goal-directed task planner. This addition to the framework would need to incorporate a memory system augmented in each robot to allow task and environment tracking. The behaviors that the robots have developed would still dominate decision making, but decisions on where to explore next would also be more influenced by where the robot has already been.

6 Conclusions

Spreading activation is an effective means of defining planning behavior for a team of robots. Once the spreading activation networks have been initialized, the robots will exhibit these behaviors independent of their place in the environment or the environment itself. However, the method of using GA evolution to find link strengths for the spreading activation network of each robot requires some *centralized method* of evaluating team fitness.

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