The Effect of Communication on the Evolution of Cooperative Behavior in a Multi-Agent System

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ABSTRACT

A team of agents that cooperate to solve a problem together can handle many complex tasks that would not be possible without cooperation. While the benefit is clear, there are still many open questions in how best to achieve this cooperation. In this paper we focus on the role of communication in allowing agents to evolve effective cooperation for a prey capture task. Previous studies of this task have shown mixed results for the benefit of direct communication among predators, and we investigate potential explanations for these seemingly contradictory outcomes. We start by replicating the results of a study that found that agents with the ability to communicate actually performed worse than those without when each member of a team was evolved in a separate population [8]. The simulated world used for these experiments is very simple, and we hypothesize that communication would become beneficial in a similar but more complex environment. We test several methods of increasing the problem complexity, but find that at best communicating predators perform equally as well as those that cannot communicate. We thus propose that the representation may hinder the success of communication in this environment. The behavior of each predator is encoded in a neural network, and the networks with communication have 6 inputs as opposed to just 2 for the standard network, giving communicating networks more than twice as many links for which to evolve weights. Another study using a relatively similar environment but genetic programming as a representation finds that communication is clearly beneficial for prey capture [4]. We hypothesize that adding communication is less costly to these genetic programs as compared to the earlier neural networks and outline experiments to test this theory.

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1. INTRODUCTION

An Evolutionary Algorithms (EA) applies the basic forces of biological evolution (differential fitness, inherited traits with variation, and natural selection) to a population of computational "genomes", each of which encodes an algorithm that attempts to solve some problem. The goal of these algorithms is to discover novel solutions to computational problems. As EAs are applied to more complex problems, it is necessary to incorporate more complex dynamics of natural evolution, such as interaction between evolving agents. Many problems that would be impossible for a single individual to solve could be solved by a population of agents working together. This leads to applying EAs to evolve the behavior of agents in a multiagent system (MAS), defined as a group of autonomous agents that interact with each other in a common environment. Several issues must be overcome in order to evolve a population of autonomous agents to cooperatively complete a task, but we focus on the question of what types of interaction should be possible between agents. In particular, we are interested in determining if and when explicit communication between agents becomes beneficial.

A major theme in MAS is emergence; complex behavior that arises at the global level due to the relatively simple actions and interactions of the multiple autonomous agents that make up the system. In many biological species, populations of individuals cooperate without any means of direct communication; technically these individuals are not even "aware" that the rest of the population exists. This type of emergent complex system behavior evolves through indirect feedback received by each organism that differs based on their individual behavior. Despite the impressive capabilities of these emergent systems, a more direct form of communication has evolved in a large number of biological species, and is an integral trait in the many social species [6]. This direct communication comes at a relatively high cost, in brain mass, development time, energy/resources expended, and the danger of giving information away to hostile or competing entities [9]. The prevalence of direct communication in the natural world implies that a communicating individual receives a benefit that outweighs the cost [2]. We hypothesize that direct communication allows for more complex cooperative interactions that are necessary to perform more complex tasks. Therefore, simpler forms of cooperation will prevail until a problem becomes sufficiently complex to require more than indirect interactions to solve.

A popular framework in which to study questions of coordination and cooperation in a multi-agent system is the predator-prey model. The details vary, but the general setup is for multiple predators to attempt to capture a single prey, where the prey can always allude any one predator so a team of predators must work together in order to succeed. Previous work on the benefit of direct communication to the success of predators in this model has yielded mixed results. Several studies have shown a clear benefit to various forms of communication [4], [3]. However others have found that in many situations simple strategies outperform more complex, general strategies such as those using communication [5], or even that providing predators with the ability to communicate is detrimental to their success [8]. We investigate these widely diverse results in an effort to discover the key factors that contribute to the successful evolution of communication.

Our initial work focuses on the experiments performed by Miikkulainen and Yong in [8]. The simulated world contained one prey agent that used a hard-coded escape strategy, and three predator agents each represented by a neural network evolved in a separate population. The incentives for the predators were designed to make cooperation clearly beneficial for the individual; the question was not whether the predators would cooperate, but rather whether or not the ability to communicate would aid their coordination. The authors found that simply enforcing separate populations is sufficient to cause a group of individuals unaware of each other to evolve different fixed roles to successfully coordinate prey capture. In fact they found that predators took much longer to evolve successful prey capture when they were given the ability to communicate with each other directly. We hypothesize that the simple environment and relatively unintelligent prey allows basic fixed-role strategies to evolve very quickly that consistently succeed in catching the prey. When these simple strategies are able to perfectly solve the problem, the ability to communicate is simply an extra burden that greatly increases the size of the search space. We raise the complexity of the environment and intelligence of the prey in several ways in an attempt to balance the cost of communication with the benefit. However, we find that communicating predators never outperform unaware predators, at best the two evolve equally well.

We therefore explore a new hypothesis that proposes the issue may be in using a neural network representation for predator behavior. In a seemingly very similar experimental setup to ours, Luke and Spector [4] found clear significant benefits to providing agents with the ability to communicate. Their work, however, used genetic programming to encode predator behavior instead of neural networks. We propose several experiments to isolate and confirm or deny that the representation difference is the key factor causing the conflicting results.

2. EXPERIMENTS AND RESULTS

2.1 Confirming Previous Results

We first replicate the original experiments of [8] with a few modifications to confirm that we see the same results given their simulation environment. The authors tested three variations of predators, one in which they could sense only the location of the prey (unaware), one in which they also could locate each other (communicating), and one in which they were all controlled by one network. We focus on only the first two types as the centrally controlled network does not relate to our study of communication. The input/output structure of the two types of networks are shown in figure 1.

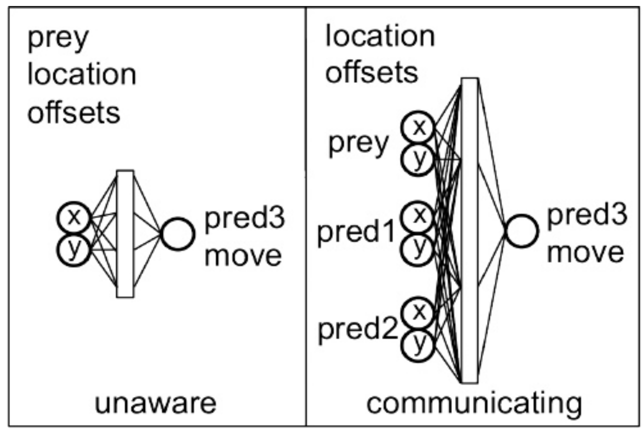

Figure 1: Input/output structure of the two types of neural networks. The outputs of a predator's network always consisted of 5 nodes, 4 representing the weight of each cardinal direction used to determine the final movement direction and 1 representing the speed at which to move. The unaware predator networks received only the x and y offsets of the prey from themselves as inputs. The communicating predator networks also received the same offsets for the prey plus the x and y offsets of each of the other two predators.

Our experiments use the same method as the original work of enforced separate populations; each predator's network evolves in a population completely isolated from the other two predators except in the step of fitness evaluation. Our modified version does not use separate populations for each neuron as in the original experiments; that method is tangential to the benefit of communication. To evaluate fitness one network is chosen from each population and the three resulting predators are all initially placed in one corner of a 100x100 toroidal world. A single prey is placed at a random position in the world, and moves at the maximum speed the predators are capable of. All agents move as if simultaneously, until any one predator reaches a distance of 1 or less from the prey (the prey is caught) or 475 steps pass (sufficient time for a predator to traverse the entire world diagonally). All 3 predators then receive the same fitness for that simulation, calculated as follows:

- If caught: 200 - (Ave. distance between the prey and each predator)

- If not caught: (Ave. initial pred-prey distance) - (Ave. final pred-prey distance)

Figure 2 diagrams the three predator populations and the simulated world.

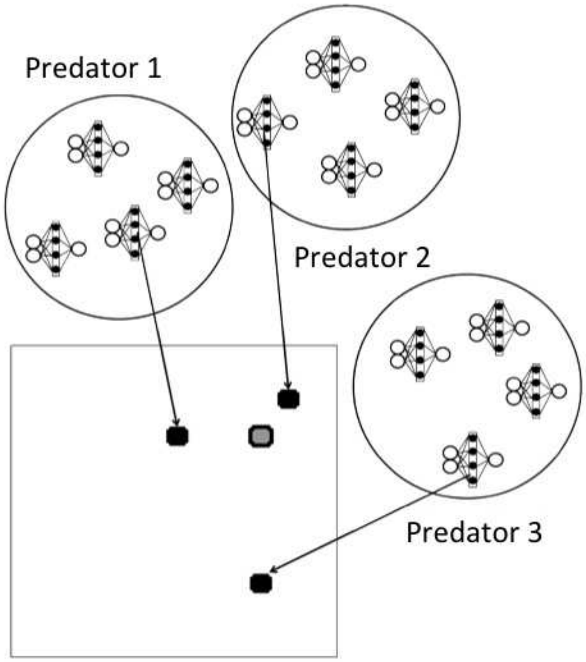

Figure 2: Diagram of the middle of a fitness evaluation. One predator network is chosen from each of the 3 populations to form a team that attempts to catch the prey in a simulated world. A single fitness value results based on the performance of the entire team and is assigned to each individual predator.

The predator populations each evolve 250 individuals. Every predator network is tested in 10 simulations, each with a different team, and the average of the 10 results determines its fitness for that generation. At the end of each generation, the most fit individual is selected from each of the three populations and the resulting team is evaluated by a benchmark test to determine the performance of the generation. The team is tested 9 times using 9 different fixed starting locations for the prey, and both the average fitness and the number of tests in which the prey is caught are recorded for that generation.

Following the method used in [8], the prey's strategy progresses through several levels of difficulty as the predators evolve. Each time the final benchmark for a generation results in the prey being caught in 7 or more of the 9 tests, the prey's escape strategy rises a level for the next generation. The strategy never decreases in level. This is necessary as otherwise the initial generations of predators can't come close enough to the prey to generate any useful selection. We experimented with coevolving the prey but it added complexity and did not result in more effective prey escape behavior than we could program by hand. The experiments in [8] used 5 levels of prey strategies, progressing from a stationary prey to one moving at full speed, although always directly away from the nearest predator. The whole task is considered solved when the prey reaches its highest strategy level and the benchmark for a generation results in the prey being caught in at least 7 of the 9 tests.

We initially allowed the neural network structure (links and hidden nodes) to evolve along with link weights, but we found that this was detrimental in this particular environment to the successful evolution of communicating predators. The initially slow prey movement means that a predator can catch the prey by running straight towards it, and indeed this solution is quickly found by unaware predators. It takes longer for the initially more complex communicating predators to also reach this solution, but the assumption is that as the prey strategy increases in difficulty, the extra complexity of communication will become worthwhile. However, when the network structure itself is allowed to evolve, the communicating networks find the solution to the initially simple capture task by removing those currently unhelpful links relating to the location of the other predators. The early evolution of these networks is largely focused on making them less complex, thus removing any future advantage they may have gained. We experimented with varying levels of structural evolution and numbers of hidden nodes and found very little difference in the results of trials with unaware predators, but a significant improvement in the performance of communicating predators when the structure was completely fixed as a fully connected network with a small number of hidden nodes (there was no significant difference between 4 and 8 hidden nodes). All of our following experiments use fixed topology, fully connected networks with 8 hidden nodes.

Table 1 shows a comparison of the original results from [8] and our results in replicating those experiments with the few changes described earlier. Our results are significantly different than those reported in [8] ($p<.01$ for both the unaware and communicating predators), but they are similar enough to seem reasonable and clearly show the same large increase in the time to evolve a solution when communication is included ($p<.001$ unaware environment solves problem in fewer generations than communicating environment).

Table 1: Comparison of original results from [8] and our results in a similar environment. The mean and standard deviation of 30 trials are given for the number of generations to catch the highest level of prey in at least 7/9 benchmark tests.

	Unaware	Communicating
results from [8]	mean=18, std=7	mean=87, std=22
our results	mean=9.5, std=3	mean=31, std=4

2.2 Increasing Complexity - More Intelligent Prey

We analyzed the strategies that evolved in our initial experiments and found that the trapping method shown in figure 3 was the most common in both communicating and unaware environments. This strategy requires only two predators to coordinate by approaching the prey from opposite sides (though the 3rd often helps in the beginning). The prey only senses the nearest predator and runs directly away from it. Therefore if 2 predators can position themselves so the prey is on the straight line between them, they can close in from either side while the prey is stuck jiggling back and forth between them, effectively sitting still waiting to be caught. The 3rd predator often helps initially to "herd" the prey onto the straight line between the other two. Other slightly different variations of this strategy evolved, but there was no apparent difference between the strategies of communicating and unaware predators.

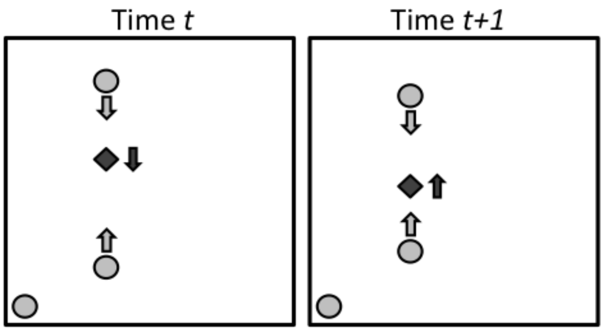

Figure 3: Diagram showing a common strategy that evolves to catch prey that runs directly away from only the closest predator. The circles represent the positions of the predators and the diamond represents the prey. The arrows show the directions each individual is moving at that time. The diagram on the left shows the state of the simulation part way through an evaluation of a predator team. In this configuration, the prey senses that the closest predator is the one directly to the north of it, and so it moves directly south. Meanwhile the two trapping predators each move one step closer to the prey. This sequence of movements leaves the prey closest to the predator directly to the south, as shown in the right diagram, and thus causes the prey to now move due north. Eventually the two trapping predators close in and catch the prey.

An examination of the evolved neural networks themselves showed that there is more nuance than we could see simply by looking at the predator behaviors in simulation.. Many communicating predators evolved the same trapping behavior as the unaware predators, but used the positions of teammates more than the position of the prey to determine their own movement. Figure 4 shows the relative weight of each input on each output for an example communicating predator's neural network. The inputs giving the location offsets of the prey, pX and pY, contribute less to the output direction than the inputs giving the location offsets of the other two predators.

Despite the fact that many predators are thus using communication, it is only a byproduct of the fact that those input nodes exist, not evidence that communication itself is actually useful in any way. Given that the same behavior can evolve to work just as well in far less time without any communication, there is simply no incentive to use communication to achieve more complex behavior. We hypothesize that we must increase the complexity of the problem in order for the usefulness of communication to outweigh its cost.

Our first method of increasing complexity stems directly from the frustration of watching the prey wiggle back and forth between two trapping predators when it could easily escape by moving away from the line between them. We

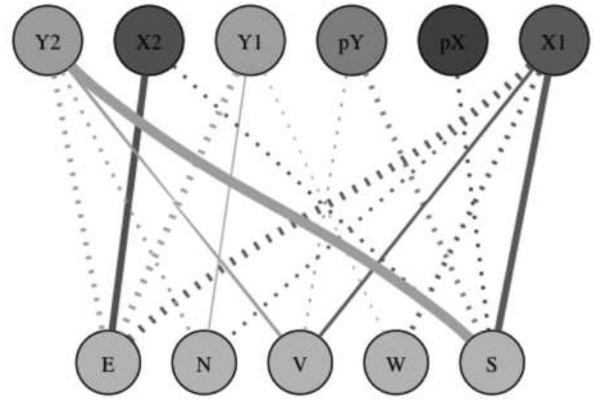

Figure 4: Simplified diagram of a communicating predator's neural network. The hidden and bias nodes are not shown, only the input and output nodes. The inputs are the location offset of the prey (pX is the offset to the east and pY is the offset to the north), and the offsets of the other two predators (X1,Y1 and X2,Y2. The N, S, E, and W outputs are the weights of the four cardinal directions used in calculating the actual direction to move, and output V is the speed of the movement. The width of the line between two nodes shows the relative contribution of that input to that output when summed over all paths between the two nodes, both direct and through hidden nodes. The wider the line, the more weight the input value will have on the final calculated output value. Solid lines represent a positive relative weight, dashed lines represent a negative relative weight. In this example the inputs for the prey location offsets have a very small influence on the final movement; the inputs for the other two predator offsets are much more important.

add 2 levels of prey strategy beyond the original 5. At the 6th level the prey continues to move at full speed, but determines the direction to move based on the positions of the two closest predators, with more weight given to the closest. This strategy takes into account the situation where the closest two predators are on opposite sides and will cause the prey to move perpendicular to the line between them. At the 7th level, the prey uses the location of all three predators to determine the direction to move, again giving closer predators higher weight. The results of this experiment are shown in table 2.

Table 2: Time to evolve solutions to 2 further difficulty levels of prey strategies. The mean and standard deviation of 30 trials are given for the number of generations to catch the stated level of prey in at least 7/9 benchmark tests.

	Unaware	Communicating
6th prey level	mean=43, std=11	mean=84, std=36
7th prey level	mean=49, std=10	mean=107, std=56

These more difficult prey strategies do increase the complexity of the problem; both the unaware and communicating predators take significantly longer to evolve solutions ($p<.01$ in both treatments that gens to solve 5th prey level < gens to solve 6th prey level < gens to solve 7th prey level). However, the communicating predators still perform significantly worse than the unaware predators ($p<.001$ unaware gens to 6th level < communicating gens to 6th level; $p<.01$ unaware gens to 7th level < communicating gens to 7th level). Once again the unaware predators were able to find fixed strategies that successfully solved the problem in a reasonable amount of time.

One common strategy that consistently catches the most difficult prey is shown in figure 5. This strategy takes advantage of the toroidal world by again having two predators trap the prey while the 3rd positions itself along the perpendicular line the prey will try to escape on, exactly half-way around the world from the prey. The prey "sees" each predator in whatever direction makes it closest, so when a predator is half-way around the world, the prey will see it coming from one direction and so move in the opposite, but that move causes the predator to be closer now in the direction just moved, so the prey moves back to the starting location. The prey now jitters in all four directions, but never gets anywhere.

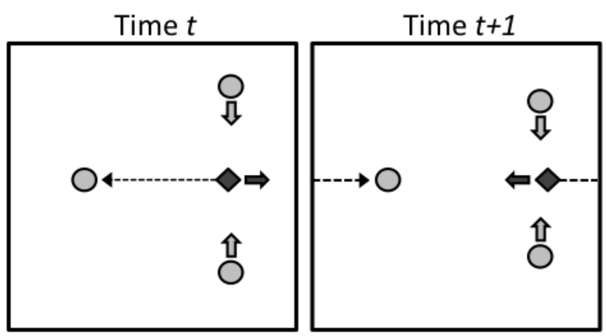

Figure 5: Diagram showing a common strategy that evolves to catch the most difficult prey. The circles represent the positions of the predators and the diamond represents the prey. The arrows show the directions each individual is moving, and the dotted line shows the line of sight from the prey to the 3rd predator. The prey runs from all three predators with more weight given to those that are closer. The 2 predators above and below the prey keep it from moving any significant amount to the north or south, just as in the earlier strategy shown in figure 3. The position of the 3rd predator is the key advance that allows this strategy to catch the more intelligent prey. In the left diagram the prey senses that the 3rd predator is to the west, as the distance to the predator is slightly shorter to the west than it is to the east. They prey therefore moves to the east, but that causes the predator to now be sensed to the east, and so the prey moves back to the west, as shown in the right diagram. Thus the prey more or less holds still while the first 2 predators close in on it.

We experimented with one more update to the prey's escape method designed specifically to thwart the predator strategy in figure 5; we actually made the prey seemingly less intelligent by limiting its sensing distance to one quarter of the world size in each direction instead of the previous one half. This limit in sight means a predator half-way around the world will have no effect on the prey at all. The new prey strategy did significantly increase the complexity of the problem, however the performance of the communicating predators degraded as much or more than that of the unaware predators. Only 7 of 14 trials evolved a team of communicating predators within 500 generations that solved the problem (success was defined as catching the highest level of prey in 7 of 9 benchmark tests). A successful team of unaware predators was found within 500 generations in 13 of 14 trials ($p<.01$ that 13/14 successes in unaware treatment is greater than 7/14 successes in communicating treatment). We returned to unlimited prey sight distance in all following experiments.

2.3 Increasing Complexity - Random Initial Positions for Predators

In the experiments described thus far, the three predators always began each fitness evaluation in the same positions in the bottom left corner of the world, though the prey's initial position was random. This placement was used to be consistent with the original experiments in [8]. The toroidal world and random prey placement mean that starting in the bottom left corner is no different than any other position, however the fact that all three predators always start together could simplify the evolution of fixed strategies in the unaware predator teams. It seems it should require more coordination to catch a prey if the three predators also begin each evaluation in random locations. Table 3 shows the results of experiments where the three predators as well as the prey began each fitness evaluation in a random location, with the constraint that the initial distance between the prey and closest predator must be at least 10.

Table 3: Results of experiments where predators begin each simulation in random positions. The mean and standard deviation of 28 trials are given for the number of generations to catch the 5th, 6th, and highest level of prey in at least 7/9 benchmark tests.

	Unaware	Communicating
5th prey level	mean=7.4, std=2	mean=27, std=6
6th prey level	mean=88, std=40	mean=115, std=51
7th prey level	mean=97, std=45	mean=123, std=55

This change causes no significant difference in either communicating or unaware treatments for the time to evolve a solution to the 5th level of prey, the highest level in the original experiments. Random starting locations for predators does make catching the 6th level of prey significantly more difficult in both treatments (in testing if number of generations to solve 6th level of prey is higher in random start experiments than in earlier fixed start experiments: $p<.01$ unaware, $p<.05$ communicating). However once a solution to the 6th level of prey is found, it takes no longer to find a solution to the highest 7th level of prey than it did with fixed predator starting locations. The unaware predators still find solutions to all levels of prey more quickly than the communicating predators, although the difference is now much smaller (in testing if unaware treatment finds solution in less generations than communicating treatment: p<.001 5th level of prey, p<.05 6th and 7th levels of prey).

A closer look at the actual strategies used shows that unaware predators take advantage of the fact that the world is toroidal to implement successful fixed strategies. The strategies themselves are almost the same as in earlier experiments, with two predators trapping the prey while the third keeps it on the line between them. The difference is that it often takes longer for the two trappers to get into the correct positions, as their fixed strategies cause them to always move in the same direction to approach the prey. When they began together, it worked well for one to always for example head west and the other east; no matter where the prey started it would immediately be between them at least on the x axis. When they begin in random locations, however, they sometimes start on the wrong sides of each other and so first move towards each other until they cross and only then really begin to trap the prey. As they have a limited amount of time to catch the prey (475 moves for each agent), they must nail down all other aspects of the strategy perfectly to make up for the lost time, whereas in the earlier experiments there was room for some inefficiency. These experiments show much closer results for communicating vs. unaware environments, but still a significant disadvantage to including the ability to communicate.

2.4 Increasing Complexity - Limited Sensing

We next experimented with a different approach to increasing the complexity of the problem; instead of increasing the escape abilities of the prey, we limit the sensing abilities of the predators. Specifically we hypothesize that if predators can only see the prey when they are close to it, but can still communicate with each other over longer distances, there should be a clear advantage to having that ability to communicate with each other. This unequal sensing distance is not unrealistic biologically, as predator to predator communication often occurs through sound that can travel long distances and through visual barriers, while a predator can only sense prey when it has line-of-site. We expect unaware predators to perform poorly in this environment, as when they cannot see the prey they have almost no information to base their actions on. However we expect that communicating predators can overcome this by using information about fellow predators who can currently see the prey.

In this setup we limit sight distance of a predator to the prey to 25 units in any direction (the world is 100x100). This means each predator can see a bit less than one half of the world. We also add 2 additional input nodes to both communicating and unaware predator networks. The first is an input that is set to 10 if the prey is in site range, or -10 if it is not. This allows predators to evolve different behavior when they can and cannot see the prey. When the prey moves from in to out of site range the x and y prey offsets remain at their last values when the prey was in range until it comes into range again. If the initial position of the prey is out of site range, the prey offsets are set to 0, so that the predator may quickly evolve initial behavior based only on the value of the new in/out range input node. We run 30 trials for each environment to 1,000 generations, as we expect it to take longer to evolve good strategies than on previous tasks. We find that neither environment is able to evolve good strategies in any amount of time; only 17/30 communicating and 15/30 unaware trials even solve the 5th level of prey, no trial from either environment solves the 6th level of prey in the 1,000 generations.

3. CURRENT AND PROPOSED WORK - GENETIC PROGRAMMING REPRESENTATION

Though we found an environment where communicating agents performed at least as well as those unable to communicate, it required making the problem so difficult that predators in both environments performed poorly. Given that several others have found communication to be beneficial in similar predator-prey models, we question why it seems so difficult to find any environment in this setup where communicating agents have an actual advantage. This is a broad question that has been and still is being explored from many angles in the MAS community, but we posit that a likely issue in our particular experiments is the use of neural networks to encode agent behavior. In experiments seemingly very similar to ours, Luke and Spector found clear significant benefits to providing agents with the ability to communicate [4]. Their work, however, used genetic programming instead of neural networks to encode predator behavior.

There have been some studies comparing the performance of genetic programming and neural network representations in specific problem domains [7], [10], [1], but we could not find a comparison such as the one we propose in this context. We hypothesize that there may be inherent aspects of neural networks that make the particular implementation of communication used in the original study [8] not a good fit for the problem. The two main issues are related; 1) adding the extra inputs for the location of other predators more than doubles the size of the neural network and thus the number of edge weights that must be optimized, and 2) there is no simple way for a predator to ignore this extra information or choose when to use it. We hypothesize that Genetic Programming (GP) is more suited to adding communication to the predator-prey problem. Adding functions that allow for communication to GP does increase the size of the overall search space, but not as drastically, and each individual genome may choose if, when, and which ones of those extra functions to use.

There are 2 other significant differences in [4] that may be factors in the success of communication in their work, either instead of, or along with the GP representation. Our current experiments are designed to isolate these three factors in order to determine how important each may be to the success of evolving communicating agents. We hypothesize that the choice of representation will be the critical factor in explaining the conflicting results. However if we find that one of the first two factors has a significant effect, that itself will be an important result and warrant further investigation. The three directions we will explore are as follows.

1. The specifics of the simulated world in [4] are somewhat different than in our previous tests. The simulations include 4 predators instead of 3, movement occurs in stepwise fashion, the prey moves 3 steps for each 1 of the predators, and the world is smaller in size. We will test the potential impact of these differences by performing our same experiments us-

ing neural networks except fitness evaluations will use the simulation world from [4].

2. Each team of predators in [4] is represented as 4 branches of a single individual, and all of these teams are evolved in a single population. However the breeding method that led to the largest benefit of communication comes close to approximating the separate populations used in our experiments. To test the importance of this difference in population structure, we will replicate the experiments from [4] both with their original single population method and with our method of each predator evolving in a completely separate population.

3. Finally we will attempt to run each of the 2 experimental setups with as little change as possible except the alternative representation. This is more difficult because so many other aspects of evolution are tied to representation, but would yield solid evidence as to whether the neural network representation simply is not suited to evolving communication in this domain.

4. ACKNOWLEDGMENTS

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