Neuro-Evolution for Competitive Co-evolution of Biologically Canonical Predator and Prey Behaviors

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Abstract— **This paper presents a simulation of predator (pursuer) and prey (evader) agents operating within a competitive co-evolution process. The aim of the study was to investigate the effects of different resource (food for the prey) distributions and amounts on the adaptation of predator (pursuit) and prey (evasion) behaviors. Predator and prey use *Artificial Neural Network* (ANN) controllers to simulate behavior, where behaviors are adapted by *Neuro-Evolution*. The research objectives were two-fold. First, to test the capability of NE for evolving predator and prey behaviors that are effective in environments other than that in which they were evolved. Second, to test the efficacy of NE as a behavioral modeling method for co-evolutionary predator-prey simulations. Results indicated that NE was effective at evolving predator and prey behaviors that also performed well in other environments. Also, NE was successful at deriving behaviors that maintained specific similarities with those reported upon in related predator-prey studies. A key goal of this research was to use a synthetic approach to elucidate behavioral evolution in nature.**

I. INTRODUCTION

The use of competitive co-evolution to facilitate emergent behavior [1], [2] via harnessing *arms race* dynamics [3], [4] is a well explored research area in pursuit-evasion tasks [5], [6], [7] and related predator-prey simulations [8], [9], [10]. However, the robustness of co-evolved behaviors in terms of task performance when transferred to other environments has received relatively less research attention.

Also, in both biological and agent-based research, there have been few studies that examine the co-adaptation of predator and prey behaviors with respect to resources in the environment [11]. Consequently little is known about how predators and prey concurrently behave in competition with one another, and in response to resources in their environment. According to ethological models, a predator is expected to spend a greater portion of its lifetime in resource patches where the prey spends a significant portion of its lifetime [12]. A prey must adapt its behavior in order to balance space use with the risk of predation and the benefits of foraging [13]. Generally prey are expected to favor resource rich patches and avoid areas with high predation risk. Hence, a predator should try to match the time spent by the prey in resource rich patches in order maximize the chances of prey capture [14]. This dynamic between resource patch selection makes it critical to study predator and prey space use concurrently, rather than studying either in isolation [11].

Agent-based models, characterized by synthetic methodologies (understanding via building) are becoming increasingly popular in animal behavior research [15]. Combining *Artificial Neural Networks* (ANNs) and genetic algorithms (*Neuro-Evolution* (NE) [16]) for evolving agent behaviors has been well researched [17], [18], [19]. Such models are analogical systems that aid ethologists in constructing novel hypotheses for biology. As in such research, we adopt the supposition that agent simulations implicitly represent hypotheses about, and should be evaluated in comparison to, biological systems [20]. Also, agent simulations allow biologists to test hypotheses and to investigate biological phenomena in the context of experiments that cannot be conducted in nature.

This paper investigates simulated predator and prey behaviors, and relates them to behaviors derived by theoretical biological models. Specifically, the time predator and prey agents spend on food patches is measured. We use a competitive co-evolution process as a means of progressively improving and adapting predator and prey agent behaviors. We co-evolved the behaviors of one predator and one prey agent. Only two agents were simulated in order to simplify the analysis of emergent pursuit-evasion behaviors. Within the competitive co-evolution process, NE was used to adapt agent ANN controllers. Previous research [21] demonstrated the efficacy of NE as a controller design method in competitive co-evolution process. In this study, behaviors adapted by NE (in different environments) were compared according to two measures. First, the number of *pursuit-evasion games won* by the predator and prey, in environments containing different resource distributions and amounts. Second, the *time spent* by agents on resource patches in environments with different resource distributions.

In terms of the overall objective, this research aimed to combine NE with an agent-based simulation in order to address two goals pertinent to biologically inspired computing. First, to demonstrate that NE is suitable for agent controller design within a competitive co-evolution pursuit-evasion task. Second, to test the efficacy of NE as a method for modeling biological phenomena in agent based simulations, where such simulations test biological hypotheses, and elucidate how behaviors emerged in nature.

A. *Research Objectives*

1) Determine the efficacy of the given NE method for co-evolving controllers that are effective (in terms of number of pursuit-evasion games won) when tested in other environments (defined by varying resource distributions and amounts).

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2) Ascertain the appropriateness of NE as a predator-prey behavioral modeling method via comparing co-evolved behaviors observed in the agent-based simulation with those observed in related predator-prey studies.

B. *Research Hypotheses*

1) Given previous research results [21], NE co-evolved predator and prey controllers will perform comparably well (in terms of the number of pursuit-evasion games won) when tested in other environments (defined by varying resource distributions and amounts).

2) Given related predator-prey behavioral models [22], for all environments, the prey will spend a portion of its lifetime on each food patch, proportional to food amounts in those patches. Predators will approximately match prey spatial distribution behavior.

II. METHODS

In this study, the competitive co-evolution process uses two populations of individuals (ANN controllers) that compete against each other, where each population aims to evolve the fittest behavior. One population adapts behaviors for predator agents, and the other adapts behaviors for prey. Within each population, behaviors compete for the role of the fittest behavior. The fittest behaviors then compete against each other in the context of the pursuit-evasion task. Each behavior is represented by a genotype, which is a vector of floating point connection weights values of a controller.

A. *Neuro-Evolution (NE)*

A competitive co-evolution version of *Conventional Neuro-Evolution* (CNE), based on that proposed by [23], was used. This method directly encoded and evolved complete controllers. That is, one genotype encodes all the parameters (input and output connection weights) of an ANN controller. After all controllers in each population have been evaluated, recombination occurs. During recombination, each controller is systematically selected from an *elite portion* (table I) of each population and recombined with a partner controller (randomly selected from the same population). Enough child controllers are produced in order to completely replace each population. A child genotype is produced via recombining two parent genotypes using single point crossover [24], and mutation with a *Gaussian* distribution. The mutation operator changes each gene (connection weight) by a random value in a given range with a fixed degree of probability (table I).

B. *Predator and Prey Genotypes*

The term *genotype* refers to a string of floating point values (a) that represents the connection weight values of a predator or prey ANN controller. Where, a directly encodes a controller, and is a string of 148 (predators) and 222 (prey) floating point values. Predator controllers consist of weights fully connecting 13 sensory input neurons to eight hidden layer to four motor output neurons (figure 1: left). Prey controllers consist of weights fully connecting 17 sensory input neurons to nine layer neurons to six motor output neurons (figure 1: right). Also, there is one bias neuron for the input and hidden layers for predator and prey controllers (not illustrated in figure 1). Each connection weight is initialized to a value in a fixed range (table I), and can change to any value during the adaptation process.

C. *Genotype Evaluation*

Each controller in a given population is systematically evaluated against 20 randomly selected opponent controllers. Opponents are selected from: (1) The opposing population, or (2) A *Hall of Fame* [2]. For each pairing of controllers, six pursuit-evasion games are played. The evaluation and assignment of fitness to all controllers in both populations constitutes one iteration in the NE competitive co-evolution process. The fitness functions used in this study is reported upon in related research [21].

III. PURSUIT-EVASION TASK

The pursuit-evasion task requires one predator agent to *capture* one prey agent. Prey capture occurs when a predator occupies the same grid cell as the prey. One predator and one prey agent are initialized to random positions in the environment, at a minimum Euclidean distance of two, and a maximum distance of 16 grid cells.

A. *Pursuit-Evasion Simulation*

The simulation uses a *tritrophic* [11] one predator versus one prey model. That is, the predator pursues the prey, and the prey evades the predator and forages resource patches for food to consume. The environment is a bounded two dimensional grid of 25 x 25 cells. One predator, one prey and any number of food units can occupy any x, y position. At each iteration of a pursuit-evasion game, agents can move in one of eight directions. Predators and prey can opt to move one grid cell per game iteration, or to stand still. To give the prey an advantage, it is also able to jump a distance of two cells per game iteration. Dissimilar to related research [14], we assume metabolic (energy) costs for the predator and prey, and resource patches offer the prey no protection from predation. Three simulation environments, containing different distributions of 70, 40 or 10 food units, were tested.

- *Corner Environment:* Spreads all food units across four patches (one in each corner). Each patch covers a 5 x 5 grid cell area. Given that 70 and 10 food amounts cannot be divided equally, left over food units are placed in the top and bottom left corner food patches. Figure 2 presents the *corner* distribution with 10 food units.
- *Clustered Environment:* Spreads 70% of food units over one *big patch* (7 x 7 grid cells) and 30% of food units over three smaller patches (of 3 x 3 cell areas). Patches are in fixed locations and do not overlap. Figure 4 presents the *clustered* distribution with 10 food units.
- *2-patch Environment:* Spreads 80% of food units over one big patch (8 x 8 grid cells) and 20% of food units over one small patch (of 4 x 4 cell areas). Figure 6 presents the *2-patch* distribution with 10 food units.

Neuro-Evolution (NE) Parameters	
Population size / Elite portion	32 / 0.5
Number of NE generations	1500
Mutation probability / rate per gene (σ)	0.05 / 1
Gene (weight) value initialization	[-1.0, 1.0]
ANN sensory input neurons (Predator / Prey)	13 / 17
ANN hidden layer neurons (Predator / Prey)	8 / 9
ANN motor output neurons (Predator / Prey)	4 / 6

TABLE I
NE PARAMETERS.

Simulation Parameters	
Iterations per pursuit-evasion game	70
Simulation runs / Games per evaluation	20 / 120
Environment width / length	25
Number of food units	70 / 40
Energy per food unit	6
Initial agent positions / energy	Random / 70
Prey jump cost / distance	4 / 2
Predator / Prey movement cost	1 / 2
Predator / Prey movement distance	1 / 2
Sensor noise (σ)	0.1
Food distribution	Corner / Clustered
Hall of Fame size / update (iterations)	15 / 50

TABLE II
SIMULATION PARAMETERS.

Tables II and I present the NE and simulation parameter settings, respectively. Parameter values were derived experimentally. Minor changes to these parameter values produced similar results (not presented here due to space limitations).

IV. PREDATOR AND PREY

A. *Detection Sensors*

Four food detection and four opponent detection sensors cover four sensor quadrants. This provides an agent with a 360 degree field of view. Each sensor quadrant is positioned at the front, back, left and right of an agent. A sensor quadrant's maximum length and width are defined as one third of the environment's width. Detection sensors are always active, and sensor values are equal to the Euclidean distance to the closest food unit or opponent.

Each food detection sensor q, returns the distance between *this* agent (v) and the location of the closest food unit in the quadrant of sensor q. If no food units are detected by q then the sensor value is equal to the maximum range of q.

Each opponent detection sensor p, returns the distance between v and the location of the closest opponent in the quadrant of sensor p. If no opponents are detected by p then the sensor value is equal to the maximum range of p.

B. *Artificial Neural Network (ANN) Controller*

A recurrent ANN [25] controller maps sensory inputs to motor outputs for predator and prey agents. The controller for the predator (figure 1: left), fully connects 13 sensory input neurons ([SI-0, SI-12]) to eight hidden layer neurons, to four motor outputs ([MO-0, MO-3]). The controller for the prey (figure 1: right), fully connects 17 sensory input neurons ([SI-0, SI-16]) to nine hidden layer neurons, to six motor outputs ([MO-0, MO-5]). For both controllers, input neurons [SI-0, SI-3] accept inputs from four food detection sensors. Input neurons [SI-4, SI-7] accept inputs from four agent detection sensors. Sensory input neuron SI-8 accepts the opponent's last position (one of eight directions) as input.

For the predator, input neurons [SI-9, SI-12] accept motor output layer neuron activation values from the previous game iteration. For the prey, sensory input SI-9 indicates if the prey is situated on a food cell. Input SI-10 indicates the current energy of the agent, and input neurons [SI-11, SI-16] accept motor output layer neuron activation values from the previous game iteration. For both the predator and prey, hidden and output neurons are hyperbolic tangent units [26]. The number of hidden layer neurons was determined experimentally, and found to enable the evolution of effective pursuit-evasion behaviors. All sensor input values are normalized to the active range of the hyperbolic function [-1.5, 1.5]. Output values are in the range [-1.0, 1.0]. After sensory input normalization, Gaussian noise (table II) was applied to each input to simulate sensor noise.

C. *Action Selection*

At each game iteration, agents can move in one of eight directions. Predator agents are able to move one grid cell per game iteration at a cost of one energy unit. Prey agents can move one grid cell per game iteration at a cost of two energy units, or jump a distance of two at a cost of four energy units. At each game iteration, agents may also opt to stand still, which uses no energy. An agent's direction of movement is calculated from the controller's *Motor Outputs* (MO-0, MO-1, MO-2, and MO-3 in figure 1), as follows.

- MO-0, MO-1:
  - If MO-0 $>$ 0.0, and MO-1 $<$ 0.0: Move backwards.
  - If MO-0 $>$ 0.0, and MO-1 $>$ 0.0: Move forward.
  - If MO-0 $\leq$ 0.0: Stand still.
- MO-2, MO-3:
  - If MO-2 $>$ 0.0, and MO-3 $<$ 0.0: Move to the left.
  - If MO-2 $>$ 0.0, and MO-3 $>$ 0.0: Move to the right.
  - If MO-2 $\leq$ 0.0: Stand still.

The prey uses two other MO nodes that operate as follows.

- If MO-4 $>$ 0.0: If the prey is on a food cell, then the prey eats and does not move.
- If MO-5 $>$ 0.2: The prey jumps.

D. *Task Performance Evaluation*

As a qualitative measure for NE evolved behaviors, we used the *number of pursuit-evasion games won*. A predator won a pursuit-evasion game if it captured the prey during the game, or if the prey depleted all energy before the game's end. A prey won a game if it was not captured and survived the maximum number of game iterations (table II).

The number of games won was calculated according to the following post-hoc process. After the completion of 20

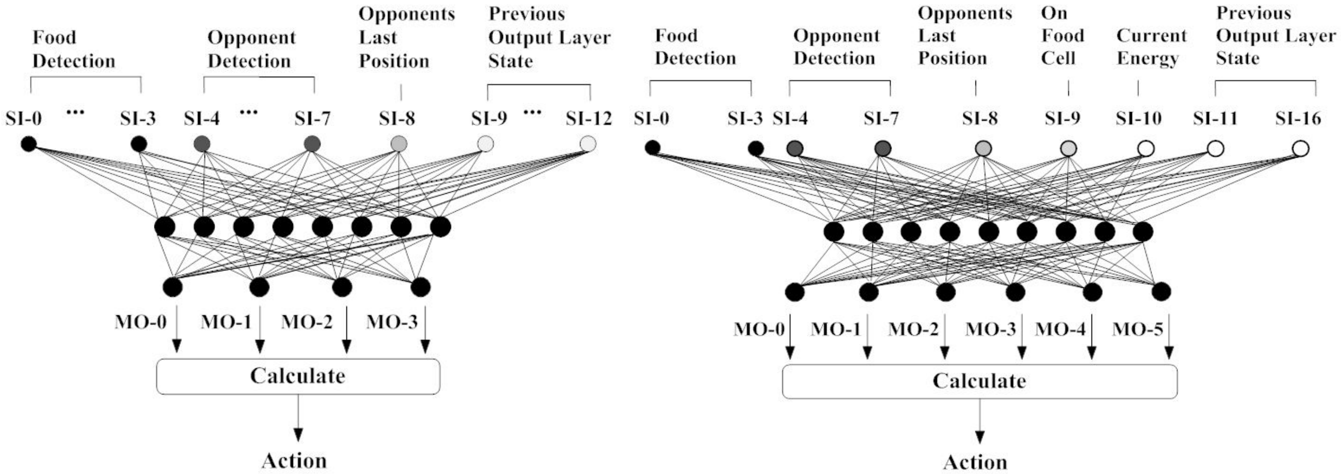

Fig. 1. Predator (left) and Prey (right) ANN controllers. *SI:* Sensory Input, *MO:* Motor Output.

runs of the NE process, the fittest predator was selected from each run. Each of these fittest predators was paired with and played against the 20 fittest NE evolved prey, selected from the same 20 NE runs. Each predator and prey pairing was executed for 100 pursuit-evasion games. No controller adaptation occurred during these games. The number of games won by the predator and prey were then calculated as a percentage of these 100 games. This process was repeated for each of the fittest 20 predators and prey.

We also measured the *time spent on food patches* by the fittest predators and prey. For each environment and food amount, the same post-hoc process was used to derive the time spent on food patches. We used this non-qualitative behavioral measure in order to relate evolved behaviors to results yielded by previous predator-prey models.

V. EXPERIMENTS

Experiments were implemented using the *Computational Intelligence Library* (CIlib)[1]. Each experiment executed the NE method for 20 simulation runs. A run was 1500 generations. One iteration consisted of a given controller being evaluated in 120 pursuit-evasion games against every controller in the opponent population. Each evaluation consisted of one agent *lifetime* (maximum game duration of 70 iterations, in table II). Experiments applied NE for co-evolving behaviors in environments containing three different food distributions. These distributions (environments) were named: *corner*, *clustered*, or *2-patch*, and contained either 70, 40 or 10 food units. In order to ascertain if there is a statistically significant difference between two data sets, we used an independent t-test [27]. Statistical significance was 0.05. The null hypothesis was that data sets do not significantly differ.

ENV: Corner (Evolved) / Clustered (Tested) / 2-Patch (Tested)		
	Predator	Prey
70 Food Units		
GW	43 / 82 / 80 (%)	57 / 18 / 21 (%)
FP	0.2 (0.2) / 0.1 (0.2) / 0.15 (0.18)	0.6 (0.1) / 0.3 (0.3) / 0.3 (0.3)
40 Food Units		
GW	72 / 90 / 88 (%)	28 / 9 / 12 (%)
FP	0.1 (0.1) / 0.1 (0.2) / 0.1 (0.2)	0.6 (0.1) / 0.3 (0.3) / 0.3 (0.3)
10 Food Units		
GW	98 / 94 / 92 (%)	2 / 6 / 1 (%)
FP	0.1 (0.1) / 0.1 (0.1) / 0.1 (0.1)	0.3 (0.2) / 0.1 (0.2) / 0.2 (0.2)
ENV: Clustered (Evolved) / Corner (Tested) / 2-Patch (Tested)		
	Predator	Prey
70 Food Units		
GW	65 / 54 / 73 (%)	35 / 46 / 27 (%)
FP	0.3 (0.2) / 0.4 (0.3) / 0.34 (0.22)	0.5 (0.2) / 0.6 (0.2) / 0.4 (0.2)
40 Food Units		
GW	83 / 76 / 82 (%)	17 / 25 / 18 (%)
FP	0.3 (0.2) / 0.3 (0.3) / 0.3 (0.2)	0.4 (0.2) / 0.6 (0.2) / 0.4 (0.2)
10 Food Units		
GW	99 / 98 / 99 (%)	1 / 2 / 1 (%)
FP	0.1 (0.1) / 0.1 (0.2) / 0.1 (0.1)	0.3 (0.2) / 0.3 (0.2) / 0.3 (0.2)
ENV: 2-Patch (Evolved) / Clustered (Tested) / Corner (Tested)		
	Predator	Prey
70 Food Units		
GW	64 / 83 / 60 (%)	36 / 18 / 40 (%)
FP	0.4 (0.2) / 0.3 (0.3) / 0.4 (0.3)	0.5 (0.2) / 0.4 (0.2) / 0.6 (0.2)
40 Food Units		
GW	86 / 89 / 88 (%)	14 / 12 / 12 (%)
FP	0.3 (0.2) / 0.2 (0.2) / 0.3 (0.2)	0.5 (0.2) / 0.4 (0.2) / 0.6 (0.2)
10 Food Units		
GW	99 / 99 / 99 (%)	1 / 1 / 1 (%)
FP	0.1 (0.1) / 0.1 (0.1) / 0.1 (0.2)	0.4 (0.1) / 0.3 (0.2) / 0.3 (0.2)

TABLE III

GAMES WON AND AVERAGE PORTION OF LIFETIME SPENT ON ANY FOOD PATCH. *GW*: PERCENTAGE OF GAMES WON. *FP:* PORTION OF LIFETIME ON ANY FOOD PATCH. *ENV:* FOOD DISTRIBUTION. *NA:* NOT APPLICABLE.

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[1] CIlib details can be found at http://www.cilib.net/.

A. *Results: Environment Comparison*

*1) **Number of Games Won.**:* Table III presents the percentage of pursuit-evasion games won by predators and prey in the *corner*, *clustered*, and *2-patch* environments (for 70, 40 and 10 food units). For each environment that an agent was evolved in, the agent was then tested in the two other environments (for 70, 40 and 10 food units). The *games won* results were derived in post-hoc experiments (section IV-D).

*2) **Test environments.**: Corner evolved agents:* Were found to be robust (in terms of the number of games won) when tested in the *clustered* and *2-patch* environments. Predators evolved in the *corner* environment won a greater number of games in the test environments. Expectedly, the opposite was the case for the prey. The exception was for predators evolved in the *corner* environment with 10 food units. These predators won approximately the same number of games (98 %) as when tested in the *clustered* (94%) and *2-patch* (92%) environments. Conversely, prey evolved in the *corner* environment won less games when tested in the other environments. The exception was for prey evolved in the *corner* environment with 10 food units (won 2% of games), and tested in the *clustered* environment (won 6% of games) with 10 food units (table III).

2-patch evolved agents: Were similarly robust when tested in the *corner* and *clustered* environments. Predators evolved in the *2-patch* environment won more or the same number of games in the test environments. The opposite case held for the prey. The exception was for predators evolved in the *2-patch* environment with 70 food units (won 64% of games), and tested in the *corner* (won 60% of games) environment (table III). Otherwise, prey evolved in the *2-patch* environment, won less or the same number of games in the test environments. The exception was for prey evolved in the *2-patch* environment with 70 food units (won 36% of games) and tested in the *corner* environment with 70 food units (won 40% of games).

Clustered evolved agents: Tested in the *corner* and *2-patch* environments won less or the same number of games in the test environments. This indicates that predators evolved in the *clustered* environment were not robust when transferred to the test environments. The opposite was true for prey evolved in the clustered environment. Table III presents the exception. Predators evolved in the *clustered* environment with 70 food units (won 65% of games), and tested in the *2-patch* environment with 70 food units (won 73% of games). Opposingly, prey evolved in the *clustered* environment and tested in the other environments won more or the same number of games. The exception was for prey evolved in the *clustered* environment with 70 food units (won 35% of games) and tested in the *2-patch* environment with 70 food units (won 27% of games).

*3) **Spatial Distribution Behaviors.**:* The average movements of the fittest predators and prey in relation to food patches in the *corner*, *clustered* and *2-patch* are illustrated in figures 2, 3, 4, 5, 6, and 7. These figures present (for 10 food units) the most traversed grid cells for agents evolved in a given environment, and then tested in the other two environments. Figures 2 - 7 were drawn from fittest agent movements derived in non-adaptive post-hoc experiments (section IV-D) . A light colored cell (approaching a value of 1.0 on the legend) indicates the most traversed grid cell, where as, a darker cell (approaching a value of 0.0 on the legend) indicates that the grid cell is never traversed. A white cross on grid cell intersections indicates a food unit.

We chose to present environments containing only 10 food units, since agent movements were the clearest in these environments, and agent movements in environments containing 40 and 70 food units were remarkably similar. Also, figures 2 - 7, present average movements when agent were within sensor range of each other. We opted to present *in sensor range* agent movements, in order to ascertain if evolved behaviors were similar to those reported upon in related predator-prey studies [22].

*4) **Time Spent on Food Patches**:* Table III presents the average time spent by the fittest predator and prey (as a portion of their lifetimes) on *any* food patch when *in* opponent sensor range. Results are reported for the *corner*, *clustered* and *2-patch* environments, containing 70, 40 and 10 food units. These results were derived in post-hoc experiments (section IV-D). The high standard deviations reported in table III (for all environments) are a result of agents spending most of their lifetime moving between food patches.

Statistical tests indicated that there was no significant difference between the *average time spent* (by predators versus prey), on *any* of the food patches when agents were evolved in any environment. Also, there was no significant difference between the time spent (by predators versus prey), when *evolved* in one environment and *tested* in another. For example, when agents were evolved in the *corner* and tested in the *clustered* and *2-patch* environments (table III). Observed spatial distribution behaviors indicated that the prey spent a portion of their lifetime on food patches proportional to the amount of food in the patches. Co-evolved predators approximately matched this behavior.

These results indicate the NE method was able to co-evolve predator and prey agents that yielded comparable behaviors (in terms of their spatial distribution) when tested in other environments. This is supported by figures 2 - 7, which illustrate prey movements as being concentrated on and around food patches and direct paths between different food patches. For example, prey evolved in the *corner* environment moved directly between the four food patches and about the environment's edges (the faint diagonal lines depicted in figure 3). As a pursuit strategy, this prey behavior was mimicked by predators via traversing the same grid cells, but with a greater frequency. This is evidenced by the boxed "X" pattern of movement illustrated in figure 2.

Prey evolved in corner environments: Spent (on average) 25% of their lifetime distributed equally over the four food patches, and the rest of their lifetime evading the predator (figure 3). Predators roughly matched prey behavior, equally distributing, on average 12% of their lifetime over the four food patches, and the rest in pursuit of the prey (figure 2).

Prey evolved in clustered environments: Spent (on average)

25% of their lifetime on the large food patch, 9% distributed equally over the three small food patches, and the rest of their lifetime evading predators (figure 5). Predators approximately matched this prey behavior, spending on average 23% of their lifetime on the large food patch, 6% split equally over the three small food patches, and the rest of their lifetime pursuing the prey (figure 4).

Prey evolved in 2-patch environments: Spent (on average) 14% of their lifetime on the large food patch, 3% on the small patch, and the remainder of its lifetime evading the predator (figure 7). Predators roughly matched prey behavior, spending on average 17% of its lifetime on the large food patch, 3% on the small patch, and the rest of its lifetime pursuing the prey (figure 6).

Time on food in test environments: There was no significant difference between the *time spent* (by predators and prey) on any given food patch in the environment in which they were evolved, versus the environment in which they were tested. This held true for all environments and food amounts. For example, prey evolved in the *corner* and tested in the *2-patch* environment (for 10 food units), spent approximately 7% of their lifetimes on the large food patch and the 1% on the small food patch. The co-evolved predator in this case spent approximately 8% of its lifetime on the large food patch, and 2% on the small food patch.

Figures 3 - 7 present movements, when agents in a given environment were *tested* in the other two environments. Figures 3 - 7 indicate that predator and prey movements in the test environments were similar to those observed for the environments in which the agents were evolved in. For example, agent movements evolved in the *corner* environment and then tested in the *clustered* and *2-patch* environments (figures 3 and 2), were very similar to behaviors observed when agents were evolved in the *clustered* (figures 5 and 4) and *2-patch* (figures 7 and 6) environments.

However, dissimilar behaviors were observed for agents evolved and tested in the *corner* environment. Figures 3 and 2 present an example of this for prey and predators (respectively) evolved in the *corner* environment with 10 food units. Figures 5 and 6 present examples for prey and predators tested in other environments with 10 food units.

VI. DISCUSSION

In terms of the *number of pursuit-evasion games won*, NE evolved controllers that yielded a performance in the test environments, comparable, to the environments they were evolved in (table III). Statistical tests indicated that, for all environments and food amounts, there was no significant difference in terms of the number of games won between environments in which agents were evolved, and environments in which agents were tested. This result supports hypothesis 1 (section I-B), and is supported by previous research [21].

Canonical spatial game models described in biological literature qualitatively predict that if there is a high predation risk (where the prey can sense the predator), then predators will tend to spend a greater portion of their lifetimes, comparative to the prey, on food patches [14], [11], [12].

This study found that when predators and prey were *in* each others sensor range, then pursuit-evasion behaviors that evolved in each environment and observed in the test environments, conformed to predictions made by canonical spatial game models. That is, the prey favored patches rich in food (*clustered* and *2-patch* environments), and the predator approximated this behavior, often spending a greater portion of its lifetime on the food patches. In the *corner environment*, the prey spent roughly equal portions of its lifetime in each patch, and the predator matched this behavior. Also, when agents evolved in these environments were tested in other environments, there was no significant difference between the time spent (by predators versus prey) on the food patches.

It is important to note that the *time spent on food patches* (FP) result reported in table III, is the average (calculated over a set of post-hoc experiments) portion of predator and prey lifetimes spent on *any* food patch. The time spent on individual food patches (by predators and prey) for each environment is not reported here due to space constraints.

When agents were *not* in each others sensor range, then different behaviors conforming to predictions made by simple distribution theory [28] emerged. Theory predicts that when not sensed by predators, the prey will approximately match the food distribution, favoring rich food patches, and the predator will randomly distribute its movements [14]. Prey evolved in each environment spent a portion of their lifetime on each food patch proportional to the food amounts in the patches. Co-evolved predators weakly favored rich food patches (for *clustered* and *2-patch* environments), and otherwise moved randomly about the environment. Also, statistical tests indicated that there was no significant difference between the average time that agents spent on individual food patches (when not in opponent sensor range), for environments they were evolved in, versus environments they were tested in. This held true for all environments and food amounts (not reported here due to space constraints).

These results support hypothesis 2 (section I-B), and are supported by predator and prey spatial distributions results from related predator-prey research that studied Pacific tree frog (*Pseudacris regilla*) tadpole prey and *Aeshna palmata* [12] and *Anax* [22] dragonfly predators.

VII. CONCLUSIONS

This study investigated an NE method as a means of behavioral modeling in a competitive co-evolution pursuit-evasion simulation. The first research objective was to test the effectiveness of co-evolved predator-prey behaviors, in terms of how well they performed in environments (food distributions) other than the environment in which they were evolved. Task performance was measured in terms of the number of pursuit-evasion games won by the predator versus the prey. The second objective was to ascertain if the given NE method was appropriate for evolving behaviors similar to those reported upon in related predator-prey studies, and for testing existing biological hypotheses.

Additionally, results indicated that NE was able to co-evolve predator and prey behaviors that were comparably

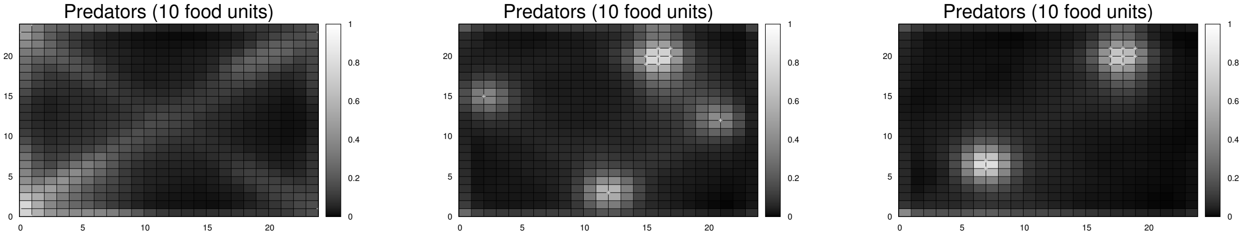

Fig. 2. *Corner Environment Predator Movements:* Evolved predator was tested in the *clustered* (middle) and *2-patch* (right) distributions (10 food units).

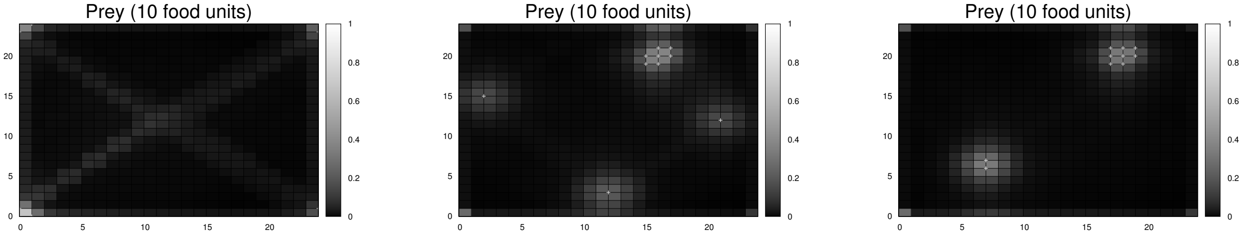

Fig. 3. *Corner Environment Prey Movements:* Evolved prey was tested in the *clustered* (middle) and *2-patch* (right) distributions (10 food units).

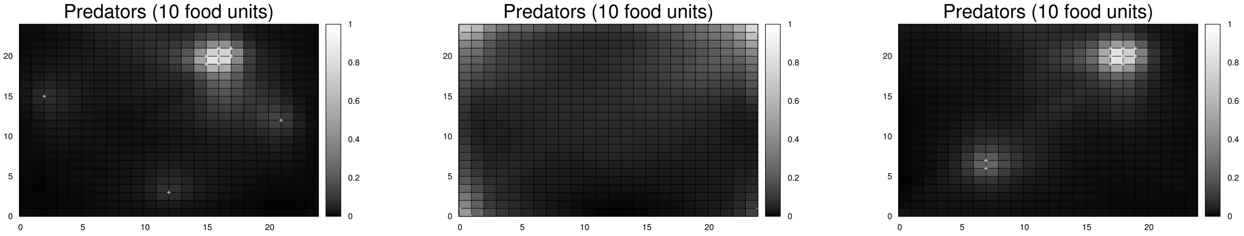

Fig. 4. *Clustered Environment Predator Movements:* Evolved predator was tested in the *corner* (middle) and *2-patch* (right) distributions (10 food units).

Fig. 5. *Clustered Environment Prey Movements*: Evolved prey was tested in the *corner* (middle) and *2-patch* (right) distributions (10 food units).

effective in test environments and the environments in which they were evolved. Also, NE evolved spatial distribution behaviors that were supported by results reported upon in related predator-prey studies. Results of this study also support the notion that agent-based simulations are an appropriate tool for exploring general principles, providing existence proofs, generating and testing novel hypotheses relevant to biology and biologically inspired computing. Thus, this study was an initial step towards using biologically inspired methods to model and simulate natural predator and prey behaviors and allow biologists to formulate new hypotheses.

Future work will implement multiple predators and prey, in order to investigate the impact of collective behavior dynamics on emergent behaviors within a competitive co-evolution process. For example, the affects of competition between prey for resources, and between predators for prey, on the co-adaptation of collective behaviors has not been well explored in agent-based biological modeling.

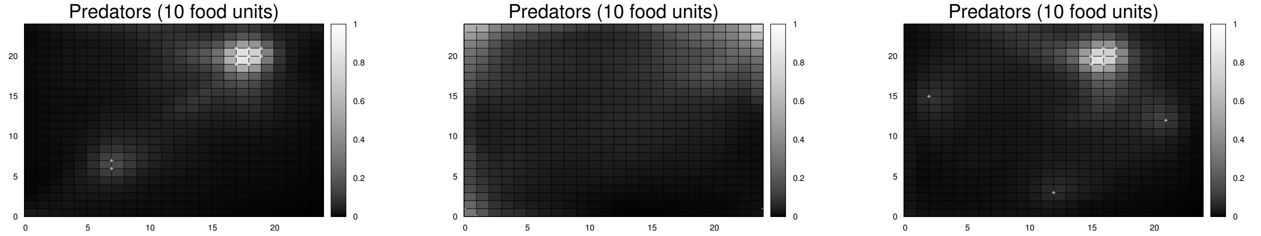

Fig. 6. *2-Patch Environment Predator Movements*: Evolved predator was tested in the *corner* (middle) and *clustered* (right) distributions (10 food units).

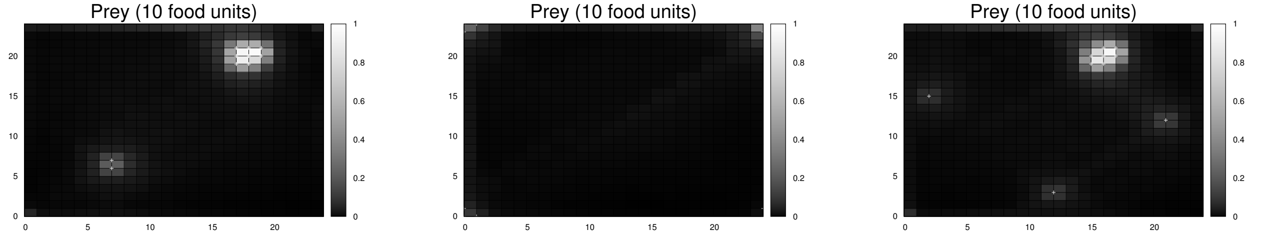

Fig. 7. *2-Patch Environment Prey Movements*: Evolved prey was tested in the *corner* (middle) and *clustered* (right) distributions (10 food units).

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