Modeling the Defense of Weak Prey Agents Against a Strong Predator Agent

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Abstract. We constructed and studied a model of interaction between a community of relatively weak prey agents and a strong predator agent in a two-dimensional grid world (a lattice environment typical of grid automata and agent-based models).

The predator can attack, kill, and consume prey agents. Each prey agent is controlled by a neural network and adopts one of two behavioral strategies: (1) normal activity, or (2) defense against the predator.

In the normal activity strategy, prey agents lie dormant, feed, breed, and move through the grid. In the defense strategy, they attempt to escape, threaten, or attack the predator. The neural network outputs control each agent's actions. The predator follows a simpler, rule-based protocol: it can lie dormant, evade threatening prey, or attack them. Its behavior is governed by basic logic.

We analyzed the model using computer simulations. We found that, with realistic parameters, the prey agents collectively overcome the predator: prey resource levels increase steadily, while the predator's resources decline to zero, leading to its extinction. We also discovered that successful defense requires a sufficiently abundant food supply; when prey food is scarce, the predator successfully suppresses the prey population. We used computer simulation to analyze the model. When the prey agents' food supply is low, the predator agent suppresses the prey agents.

Keywords: prey agents, predatory agent, prey-predator struggle.

1. Introduction

Models of interaction between autonomous agents have been studied since the early 1990s [1, 2]. For example, L.S. Yaeger [3] and D. Ackley et al. [4] studied populations of competing agents. M. Burtsev et al. [5] researched a rather complex model of evolutionary self-organization and speciation in a population of agents. In some cases, a group of relatively weak agents fights against a stronger agent. It is similar to the attack of a large flock of starlings on a sparrowhawk described by K. Lorenz [6]. V.G. Red'ko et al. [7] created and studied a computer simulation model of interaction between two groups of autonomous agents competing for the territory. It was demonstrated that a successful attack on the agents from an alien group leads to an expansion of the territory occupied by the attacking group. This paper considers a model of interaction between a sufficiently large group of relatively weak prey agents and a strong predator agent in a grid world.

2. Model Overview

Suppose that there is a society of relatively weak prey agents in the grid world. There is also a strong predatory agent. The predator agent can attack, kill, and eat the prey agents. The embedded control system of the prey agent is a simple neural network.

The predator agent has no embedded neural network control system. Its behavior is governed by simple logic presented below.

The world is a 1D chain of cells with the number of cells limited to N. The world is closed: if we move to the right beyond the N^{th} cell, we get to the 1^{st} cell; if we move to the left beyond the 1^{st} cell, we get to the N^{th} cell. Each cell may contain more than one agent.

The cells also have food for the prey agents. The number of cells with food is M. The world time is discrete: $t = 1, 2, \ldots$ At the initial moment ($t = 1$) the food elements are randomly distributed across the cells. When $t = 1$, all prey agents are at random cells. The synapse weights of the neural networks of the prey agents are also random. It is assumed that the number of prey agents N_a does not exceed a limit: $N_a <= N_{amax}$.

Let us describe the actions of the prey agents. In each time increment, each prey agent performs one action. The actions of the prey agents are governed by their neural networks.

In a peaceful strategy, the prey agents can: (1) rest (do nothing); (2) feed; (3) move to neighboring cells; and (4) breed.

In a defense strategy, the prey agents can: (1) escape from the predator agent (if the prey agent finds the predator in the same cell, it moves to a neighboring cell); (2) threatening the predator agent; (3) attacking the predator agent (only if both the prey and predator agents are in the same cell).

Each agent has some resources (energy budget).

When a prey agent feeds on the food in its cell, the energy budget is replenished. Other actions spend the energy and reduce the agent's budget. If the energy budget goes negative, the agent dies.

With the "rest" action, the consumption of the prey agent energy is lowest.

The feeding occurs as follows. If there is food in the cell in which the prey agent is located, the agent eats that food. When the neural network orders to feed but there is no food in the prey agent's cell, the agent spends a small amount of energy identical to the "rest" action. If there is food in the cell, the prey agent eats all the available food at once. Once an agent eats food in its cell, a new food element appears in another randomly selected, food-free cell. This rule maintains the number of food elements constant.

The "move" action is moving to a neighboring cell. The direction is random.

When a prey agent breeds, the child agent appears in the same cell as the parent agent. A child is born if the total number of agents N_a is less than N_{amax}. When a new agent is born, the parent agent donates half of its energy budget to the child agent. The synapse weights of the child's neural network are equal to that of the parent's neural network with some small mutations.

Upon consuming a food element, the energy budget of the prey agent is increased by Δr_1. A prey agent's energy consumption for rest, moving to a neighboring cell, threatening the predator agent, and attacking it are Δr_2, Δr_3, Δr_4, Δr_5, and Δr_6, respectively. We assume that $\Delta r_2 < \Delta r_3 < \Delta r_4 < \Delta r_5 < \Delta r_6$.

The predator agent can: (1) rest (do nothing); (2) move to the neighboring cells to evade the threatening prey agents; (3) attack a prey agent in the same cell. If a prey agent's energy budget when attacked (and killed) by the predator goes negative, the prey agent is assumed to be eaten by the predator.

The predator's energy gain from eating a killed prey agent is ΔR_1. The predator agent's energy consumption for rest, moving to a neighboring cell, and attacking a prey agent are ΔR_2, ΔR_3, and ΔR_4, respectively. We assume that $\Delta R_2 < \Delta R_3 < \Delta R$.

Let's consider the predator agent's logic in detail. In each time increment, the predator agent performs one action as follows:

(1) The predator agent first estimates the number of threatening prey agents in its cell and the right and left neighboring cells. If the number of prey agents in the predator's cell is greater than in the neighboring cells, the predator *moves* one cell to the side where the number of threatening prey agents is smaller; if this number is the same on both sides, the predator chooses the side to move randomly. Additionally, with a certain probability P_{move} the predator can move to a cell with fewer threatening prey agents regardless of the number of the threatening agents in the predator's cell.

(2) If the predator does not evade the threatening prey agents, and there are prey agents in the predator's cell, the predator *starts fighting* the prey agents: it *attacks* a randomly selected prey agent in the predator's cell. If there are also prey agents in the cell ready to fight, they all engage in a fight against the predator. The fight reduces the energy budgets of both the prey agent (attacked by the predator) and the predator (for the energy consumption values please refer to equations (2), and (3) below). If a prey agent's energy budget goes negative (the prey agent dies), the predator agent eats it, and the predator's energy budget increases significantly. If the predator agent's energy budget goes negative, the predator dies.

(3) If the predator agent does not move away from the threatening prey agents or does not engage in a fight with them, it takes the "*rest*" action.

The predator agent's priorities are: (1) move; (2) fight; and (3) rest.

Consider the loss of the agents being attacked.

The energy loss of any agent after a hit(s) is proportional to the total strength of the hits received. For a prey agent, the loss is $\Delta r_D = k_1 F_P$, where F_P is the strength of the predator's hit; k_1 is the proportionality factor (common value for all hits). For the predator agent, the loss is $\Delta R_D = k_1 F_S$, where F_S is the total strength of all hits by the prey agents attacking the predator at the moment. The strength of an individual is assumed to be proportional to the loss of the attacker's energy. For the predator agent, the strength is $F_S = n_F k_2 \Delta r_6$, where n_F is the number of prey agents attacking the predator at the moment, and k_2 is another proportionality factor. Summarizing the above equation, we obtain that the energy loss of a prey agent when it hits the predator agent is:

$$\Delta r_D = k_1 k_2 \Delta R_4 = k \Delta R_4 , \quad (1)$$

The predator agent's energy loss is:

$$\Delta R_D = k_1 n_F k_2 \Delta r_5 = k n_F \Delta r_5 , \; k = k_1 k_2 . \quad (2)$$

That is, it is sufficient to introduce just one proportionality factor k to characterize the agents' energy losses. The number of prey agents n_F simultaneously hitting the predator agent is determined by their actions invoked by their neural network control systems.

Let us consider the *sensory signals* arriving at the inputs of the neural networks of the prey agents. These signals are:

(1) The agent's energy budget.

(2) The total number of prey agents in the nearest neighborhood of the agent (in the same cell and the two neighboring cells on the right and left; it is a single combined signal).

(3) Presence of food in the agent's cell.

(4) Presence of food in the cell on the right

(5) Presence of food in the cell on the left

(6) Presence of the predator in the agent's cell.

(7) Presence of the predator in the cell on the right

(8) Presence of the predator in the cell on the left

Therefore, there are 8 input signals and 8 inputs to the neural network of the prey agent.

Now let us describe the neural network. The outputs of the neural network control the agent's actions. The neural network has a set of synapse weights **W**. This is a single-layer artificial feed-forward neural network. To describe its operation, we will use the approach proposed in [5]. To calculate the values of the output vector **O**, the input vector I is multiplied by the weight matrix **Wk** whose values are bounded by the [-W_{max}; W_{max}] range:

$$O_j = \sum_i w_{ij} i_i. \quad (3)$$

The output vector **O** contains 7 components representing the following prey agent's actions:

(1) rest (do nothing)

(2) feed

(3) move to one of the neighboring cells

(4) breed

(5) escape from the predator agent by moving to a neighboring cell

(6) threaten the predator agent

(7) attack the predator agent.

At each time increment, the prey agent performs one of these actions. Usually, it is the action corresponding to the max output O_j. Besides that, with a certain probability P_{rand} a prey agent can perform another action selected randomly. More specifically, with $1 - P_{rand}$ probability the action is the one corresponding to the maximum output of the neural network, and with P_{rand} probability, the action is random. For random actions, the probabilities of selecting each of the 7 possible actions are equal. Note that P_{rand} differs for different agents and changes as the population of prey agents evolves.

The synapse weights are also adjusted in the course of evolution. The initial synapse weights of the prey agent neural networks (at $t = 1$) are random: it is assumed that the w_{ij} values are uniformly distributed in the [$-W_{max}$,$+W_{max}$] range. Once a child of a prey agent is born, it inherits the synapse weights of the parent agent's neural networks with small mutations: each weight in the parent's weight matrix is modified by adding either $-P_M$ or $+P_M$ with equal probability. The P_M value represents the rate of mutations. The synapse weights cannot be beyond the acceptable [$-W_{max}$,$+W_{max}$] range.

The probability of randomly selecting a P_{rand} varies as follows.

The initial P_{rand} values at $t = 1$ for all agents are identical: P_{rand} ($t = 1$) = P_{rand0}. Then the P_{rand} values change during breeding: they are inherited in some variations. For a child agent, a value uniformly distributed in the [$-P_r$, $+P_r$] range is added to the P_{rand} of the parent agent. The P_{rand} values cannot exceed the [0, 1] range. Note that random selection of actions is similar to noise or random evolution and optimization of the prey agent behavior. Intuitively, a higher rate of random search can be beneficial when the agent's behavior is far from optimal. Otherwise, the rate can be reduced.

We used computer simulation to analyze the model.

At the initial moment, we defined a grid world with some food in the cells. All prey agents and the predator were put into the cells. The food elements and the agents were randomly placed in the cells. Next, initial neural networks of the prey agents were built. For each prey agent, we specified the probabilities of randomly selecting the action P_{rand} ($t = 1$) = P_{rand0}. Then the agents operated as described above.

Since some of the prey agents may die from predator attacks or due to dropping the energy budget below zero, we counted the "live" agents in the population at each time increment. If the number of agents became less than the initial population size of prey agents $N_a(t = 1) = N_{a0} = 100$, we added new agents. The positions and synapse weights of these new agents were randomized. The energy budget and probability of randomly choosing the action P_{rand0} were equal to that of a prey agent in the initial population.

The control systems of the prey evolved, and the agent population self-organized. There was no training. It was a pure evolution and survival of the fittest agents.

3. Computer Simulation Results

3.1. Basic Simulation Parameters

The size of the grid world is $N = 50$ cells.

The number of cells with food is $M = 25$.

The initial population of prey agents is $N_a(t = 1) = 100$.

The max number of prey agents is $N_{amax} = 200$.

The max value of the synapse weight $W_{max} = 1$.

The mutation rate, which represents the parent-child changes in the synapse weights is $P_M = 0.03$.

The initial probability of randomly selecting an action is $P_{rand0} = 0.3$.

The variation of the parent-child probability of randomly choosing an action is $P_r = 1$.

The probability of the predator evading the threatening prey agents (see the predator agent behavior above) is $P_{move} = 0.5$.

A prey agent's energy gain after eating a food element is $\Delta r_1 = 0.1$.

A prey agent's energy loss for resting is

$\Delta r_2 = 0.005$.

A prey agent's energy loss for moving by one cell is $\Delta r_3 = 0.01$.

A prey agent's energy loss for breeding is $\Delta r_4 = 0.02$ (besides that, a parent agent gives half of its energy budget to the child).

A prey agent's energy loss for threatening the predator is $\Delta r_5 = 0.03$.

A prey agent's energy loss for hitting the predator is $\Delta r_6 = 0.05$.

The predator's energy gain when eating a killed prey agent is $\Delta R_1 = 1$.

The predator's energy loss for resting is $\Delta R_2 = 0.01$.

The predator's energy loss for moving by one cell is $\Delta R_3 = 0.02$.

The predator's agent energy loss for hitting a prey agent is $\Delta R_4 = 0.5$.

The initial energy budget of a prey agent is $r(t = 1) = 1$.

The initial energy budget of the predator agent is $R(t = 1) = 10$.

The proportionality factor k, which represents the agents' energy losses when they are hit (refer to equations (1), (2) above) is $k = 1$.

Note that some parameters were varied during the computer modeling. The results of this variation are covered separately.

3.2. Dynamics of Prey Agents Population in the Presence of a Predator. Basic Simulation

We analyzed how the following variables vary in time: the population-average energy budget of a prey agent $r(t)$, predator's energy budget $R(t)$, the number of prey agents performing any of the 7 actions, the share of actions performed by the predator at a given moment, the number of prey agents dead by the current time increment N_{ad}, the total number of prey agents, the average probability of a random selection of an action P_{rand} (t). We simulated 1,000 time increments. All the resulting time dependencies were averaged over 1,000 simulation runs.

Fig. 1 shows the population-average energy budget of the prey agents and the predator energy budget vs. time.

As can be seen from Fig. 1, after a short initial period (when $t < 200$), the energy budget of the prey agents grows steadily. The predator's energy budget first grows and then drops to zero. Initially, the prey agents often die and get eaten by the predator, so the predator's energy budget grows at first. Subsequently, the predator's energy budget decreases, and at $t = 831$ the predator dies in all 1,000 independent simulation runs.

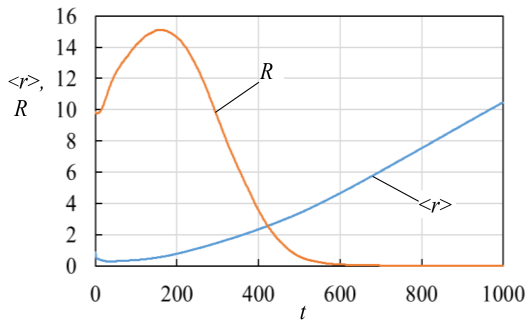

Fig. 1. Population-average energy budget of the prey agents <r> and predator's energy budget R vs. time t.

Fig. 2 shows the number of prey agents' actions vs. time for a peaceful strategy (rest, feed, move to neighboring cells, breed).

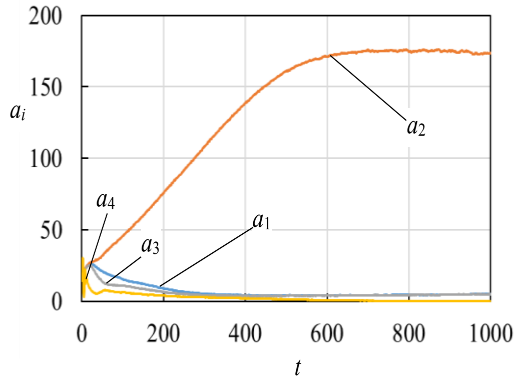

Fig. 2. The number of prey agents' actions vs. time for a peaceful strategy: rest (a_1), feed (a_2), move to neighboring cells (a_3), and breed (a_4).

It can be seen that at the very initial moments, the prey agents intensively breed and spend their energy budgets including the parent agents giving half of their budgets to children. The analysis of the computer simulation results indicates that rather quickly the agents stop having sufficient energy for breeding, and the breeding rate falls. Fig. 2 also demonstrates that the number of "feed" actions grows intensively in time and becomes predominant.

Fig. 3 shows the number of prey agents' actions vs. time for the defense strategy (evading, threatening, attacking the predator agent).

Figs. 2, and 3 show that at the initial moments, the actions of the prey agents are rather chaotic. Only after $t \approx 800$, the distribution of prey agents' actions stabilizes. Note that Figs. 2, and 3 show the agent's intended actions of feeding and attacking the predator. A real attack on the predator occurs only under certain conditions: (a) the predator must be in the same cell as the prey agent, and (b) the predator (like a prey agent) must also attack the prey agent. The "feed" action also occurs under a certain condition: when there is a food element in the cell occupied by the prey agent.

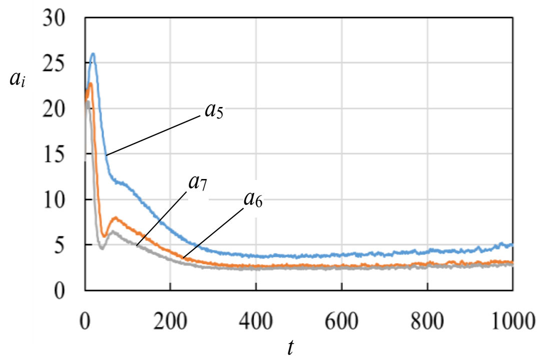

Fig. 3. The number of prey agents' actions vs. time for the defense strategy: evading (a_5), threatening (a_6), and attacking the predator (a_7).

Fig. 4 shows the share of the predator's active actions (evading threatening prey agents, hitting prey agents, resting) for 1,000 cases.

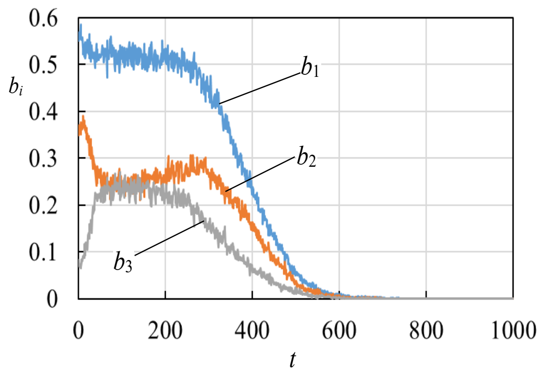

Fig. 4. The share of the active actions of the predators engaged with the prey agents vs. time t: evading threatening prey agents (b_1), attacking a prey agent (b_2), resting (b_3).

The number of deceased prey agents vs. time is shown in Fig. 5.

The total number of prey agents vs. time is shown in Fig. 6.

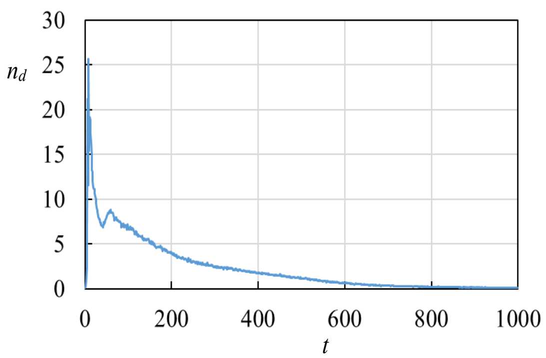

Fig. 5. The number of dead prey agents vs. time t.

Fig. 7 shows the probability of randomly selecting an action P_{rand} (t) for the prey agents vs. time. It can be seen that in the initial moments, the intensity of the random search for an action is high. As time passes, the intensity decreases. This is similar to the "gene-mutator" model [8], which assumes that the mutation rate can vary and be inherited. If a population enters a new environment, where active random search for new properties is advantageous, the mutation rate increases, while during prolonged residence in a stable environment, where preservation of already attained properties is more important, the mutation rate decreases.

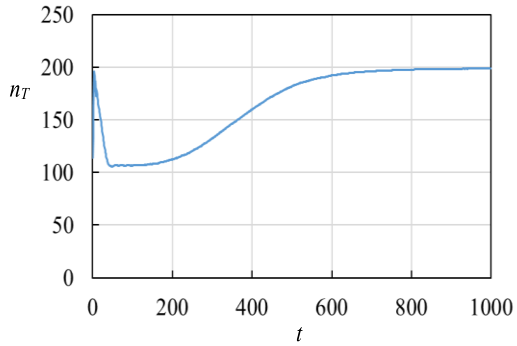

Fig. 6. The total number of prey agents n_T vs. time t.

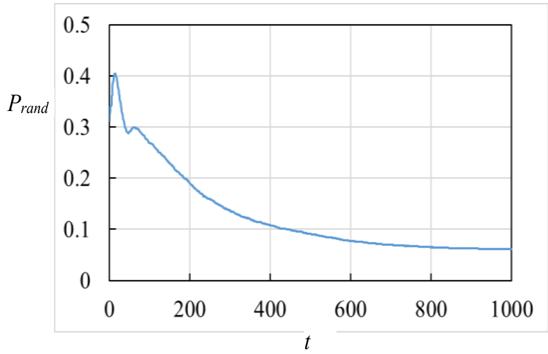

Fig. 7. The probability of randomly selecting an action P_{rand} (t) for the prey agents vs. time t.

3.3. Parameter-Varying Simulation

We ran 3,000 such simulations and averaged the results over 100 independent runs.

We varied the grid world size. For the basic simulation, the world size was $N = 50$ cells. When we reduced it to $N = 10$ cells, the dependences were similar to the ones above for $N = 50$. The significant changes for $N = 10$ are as follows: the number of the prey agents' "feed" actions decreases slightly; (2) the energy budget of the prey agents at $t = 1{,}000$ decreases significantly to $r(1{,}000) \approx 6.6$, while at $N = 50$ it is $r(1{,}000) \approx 10.5$ (refer to Fig. 1). This can be interpreted as follows. When the world is small, the prey agents have less food, so their energy budgets decrease.

When the world size increases to $N = 100$ cells, the time dependencies are similar to the $N = 50$ case. The changes are as follows: (1) for 100 independent simulation runs, in all cases the predator dies before $t = 1{,}746$; (2) the prey agents' energy budget at $t = 1{,}000$ decreases to $r(1{,}000) \approx 2.3$. We also observed that at $N = 100$, sometimes the foo elements were distributed unevenly: (a) there were cell chains (approximately 10 cells long) with no food at all; (b) there were cell chains with food in each cell. Similar results were reported in [9]. Due to such an uneven distribution, the prey agents had difficulty finding food and therefore had a radically reduced energy budget compared to the $N = 50$ case.

We also ran simulations with fewer food elements than in the main analysis ($M = 25$). We considered $M = 20$, $M = 15$, $M = 10$ ($N = 50$ for all cases). At $M = 20$, the results only change slightly: the prey agents' energy budget decreases (at $t = 1{,}000$ it is $r(1{,}000) \approx 6.4$) and the predator's lifespan changes slightly (at $t = 925$ the predator dies in all 100 independent simulations). At $M = 15$, the situation changes significantly: the prey agents' energy budget decreases significantly, and the predator agent survives up to $t = 3{,}000$. The prey agents' and predator's energy budgets for $M = 15$ are shown in Fig. 8. At $M = 10$, the variations of the variables change drastically: the predator survives until $t = 3{,}000$ in all 100 independent simulations, and with time the predator's energy budget increases to $R(3{,}000) \approx 150$, while the prey agents' energy budget decrease to $r(3{,}000) \approx 0.2$, i.e. in this case the predators actively feed on the prey agents, replenishing their energy budgets, and suppress the "life" of the prey agents.

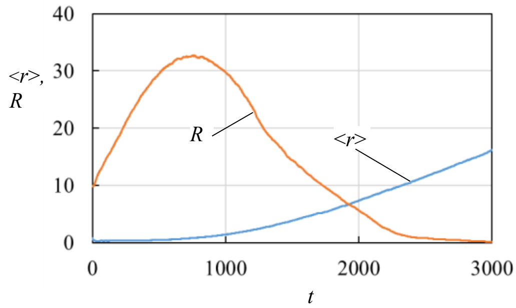

Fig. 8. Population-averaged prey agents' energy budgets <r> and predator energy budget R vs. time t. The number of food elements is reduced to $M = 15$.

4. Conclusion

We created and analyzed a computer simulation model representing a collective defense by weak prey agents against a strong predator agent. It is shown that a group of prey agents is able to resist a strong predator agent. In particular, prey agents can threaten and collectively attack the predator. By evading threatening prey agents, and repelling their attacks, the predator loses its energy and may die. We also demonstrated that prey agents need a fair amount of food to be able to defend themselves. Given enough food, relatively weak prey agents overwhelm a strong predator. When the prey agents' food supply is low, the predator agent suppresses the prey agents.

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Модель обороны коллектива слабых мирных агентов от сильного агента-хищника

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Аннотация. Построена и изучена модель взаимодействия сообщества относительно слабых мирных агентов в клеточном мире с сильным агентом-хищником. Агент-хищник может нападать на мирных агентов, убивать и съедать их. Внутренняя система управления мирного агента представляет собой нейронную сеть. Имеются две стратегии мирных агентов: 1) обычная мирная жизнь, 2) оборона от сильного агента-хищника. В первой стратегии мирные агенты выполняют следующие действия: находиться в состоянии покоя, питаться, размножаться, перемещаться по миру. Во второй стратегии действия мирных агентов таковы: уход от агента-хищника, угроза агенту-хищнику, нападение на агента-хищника. Выходами нейронной сети являются сигналы, определяющие действия мирного агента. Агент-хищник выполнять следующие действия: находиться в состоянии покоя, уходить от угрожающих мирных агентов, нападать на мирных агентов. Повеление агента-хищника определяется простыми логическими правилами. Анализ модели производился путем компьютерного моделирования. Показано, что при достаточно естественном выборе параметров модели коллектив мирных агентов побеждает агента-хищника, а именно, с течением времени ресурс мирных агентов уверенно растёт, а ресурс

агента-хищника в итоге уменьшается до нуля, т.е. агент-хищник погибает. Также продемонстрировано, что для обеспечения способности к такой обороне, мирным агентам нужно достаточно большое количество пищи. При малом количестве пищи мирных агентов агент-хищник подавляет мирных агентов.

Ключевые слова: мирные агенты, агент-хищник, борьба между агентами

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