Evolving Social Behavior of Caribou Agents in Wolf-caribou Predator-prey Pursuit Problem

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Abstract

The objective of our research is to investigate the emergent successful escaping behavior, evolved automatically via genetic programming (GP), of a team of prey (caribou) agents in Wolf-caribou Predator-prey Pursuit Problem (WCP). WCP is originally defined and investigated by Tian, Tanev, and Shimohara and can be viewed as a reversed instance of the well-studied predator prey pursuit problem. The proposed instance of WCP is a multi-agent system, in which a team of inferior prey (caribou) agents is required to escape from a single superior predator (wolf) in an unlimited two-dimensional simulated world.

Moreover, we are interested in verifying whether some socio-psychological aspects, introduced in the behavior of caribou agents would result in (i) an improved efficiency of both of the evolution of their escaping behavior and (ii) the effectiveness of this behavior. Our research could be summarized in the following three important points:

(1) From the viewpoint of *evolutionary psychology*, we investigated the survival value of the *empathy* exhibited by the caribou agents. The empathy is introduced as the following information, available to each caribou agent: (i) which peer caribou is chased by the wolf, (ii) whether the chased peer caribou is exhausted (and, therefore, needs a help). Also, we researched on the effect of *consciousness* of the caribou agents on the effectiveness of their escaping behavior. The consciousness is implemented in our work as an ability of caribou agents to understand whether they are currently being chased by the wolf.

(2) From *philosophical* viewpoint, we conducted research on the survival value of the number ("critical mass") of the caribou agents that allows a transition from quantity into quality ("*the whole is more than the sum of its parts*") of their escaping behavior.

(3) From *system designers'* viewpoint, we investigated the dilemma between the reactiveness and pro-activeness of the behavioral architectures of caribou agents. Moreover, we researched the effect of morphological and behavioral fuzziness of the caribou agents on the efficiency of evolution of the escaping behavior of caribou agents and the effectiveness and robustness such a behavior.

In our research for the evolution of the behavior of caribou agents we used the in-house XML-based genetic programming framework (XGP).

The experimental results verified that the empathy improves both the efficiency of evolution of escape behavior and the effectiveness of such behavior. In the experiments we consider a team of eight caribou agents. We employed the empathic caribou agent and obtain the experimental results with the caribou group size equal to 1, 2, 4, 8 and 10. The experimental result shows that the quantity (number of caribou agents) yields a corresponding quality (i.e., a successful escaping behavior) in that both the efficiency of evolution and the behavioral effectiveness improved with the increasing of the size of the team of caribou agents; however when the caribou group size is too high (i.e., the population density of caribou is too high), both the efficiency of evolution and the behavioral effectiveness somehow deteriorate. Also, we found the most important perception is the superposition of the consciousness and self-consciousness of the caribou. The experimental result demonstrated that only consciousness and only self-conscious alone are contributing to the better survival of the caribou agents. However, when the consciousness and self-conscious are combined together, both the efficiency of evolution and the effectiveness of the behavior of caribou agents improves significantly, suggesting a super-additive effect of these two features.

The results of the investigation of the dilemma between pro-activeness and reactiveness in the behavior of caribou agents indicate that neither a pure reactiveness nor deep pro-activeness can improve the efficiency of evolution and the effectiveness of the escaping behavior of caribou. Rather, a trade-off of these two extreme behavioral features results in best-performing team of caribou agents.

Finally, the experimental results on the incorporation of the fuzziness of the sensory- and moving abilities of caribou agents demonstrate that this fuzziness indeed facilitates a better efficiency of evolution and an improved robustness to a realistically simulated perception noise.

In our future work we are planning to i) investigate the effect of dithering on the efficiency of the escaping behavior of caribou agents in the proposed WCP, ii) improve the fuzzy model of caribou agents, and iii) employ co-evolution to evolve the behavior of both the wolf agent and the caribou agents.

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Introduction

1. 1. Background

As ancient Greek philosopher Aristotle (384 BC – 332 BC) noted, "The whole is greater than the sum of its parts." This principle applies particularly well to various aspects of science, technology, and engineering. In our research, we attempted to verify this principle in the domain of multi-agent systems (MAS) that model an artificial society. Moreover, we also investigated whether socio-psychological aspects implemented in caribou agents –such as empathy, grouping (swarming) and the way of solving the dilemma between reactiveness and pro-activeness – improve the efficiency of the simulated evolution of their behavior or the effectiveness of such a behavior.

1. 2. Objective of Research

The *objective* of our research was to investigate the feasibility of applying genetic programming (GP) to automatically evolve the escape behavior of a team of caribou agents. Moreover, we also examined whether some socio-psychological aspects – such as empathy, grouping (swarming), self-conscious, the trade-off (dilemma) between reactiveness and pro-activeness – introduced in caribou agents improved the efficiency of their simulated behavioral evolution or behavioral effectiveness.

In our previous research, we implemented empathic caribou agents and demonstrated the feasibility of applying artificial evolution (via GP) to automatically develop the escape strategies of the team of such agents in the WCP. Furthermore, we verified the importance of the size of the caribou team, and demonstrated the survival value of empathy in that the latter significantly improves both the efficiency of evolution of the escape behavior and the effectiveness of such a behavior.

In our current research, we shall consider the surviving effects (if any) of the introduction of swarming behavior in caribou agents. In addition, we will investigate the implications of the dilemma between the reactiveness and pro-activeness of caribou agents on the efficiency of evolution of their escape behavior.

1. 3. Motivation of Research

Firstly, in MAS area, we are interested to find a research tool for collective intelligence and emergent behaviors through interactions and communications between agents.

Secondly, in application area, we are interested in problem solving, simulation, collective robotics, software engineering, and so forth.

Moreover, we are interested to find the reasons why during the millions year's evolution, not only us human beings but also the animals emerged numerous social behaviors. In other words, we are interested in simulating some socio-psychological aspects which have not been researched and investigate the survive value of such socio-psychological aspects.

To sum up, we are interested in construction of synthetic worlds, focusing on the autonomy of agents and the interactions that link them together.

1.4. Limitation and Challenges

One of the major challenges in developing a functional team of caribou agents in WCP is the implementation of the escape behavior of these agents. In principle, we can develop the behavior of caribou agents by applying a top-down approach and handcrafting the mapping of the current environmental state, available to the agents (i.e., their perceptions), into desired actions. However, due to the significant behavioral complexity of the multi-agent system of WCP, we would be unable to infer the required behavior of the individual entities (caribou agents) from the desired team-level escape behavior. The relationship between the properties at these two levels (i.e., entity-level and team-level) is non-linear, very complex, and too difficult to be formalized. Hence, we rely on GP, which is both a heuristic and holistic approach, to develop such behavior.

Another significant challenge, which is rather specific of the considered case of the WCP, is to ensure that the escaping caribou agents stay “in touch” with each other in order to cooperate during the entire duration of the escape behavior. In other multi-agent systems that model various aspects of behavior of agents in artificial societies (e.g., herding, surrounding, capturing, etc.), the successful behaviors of entities usually exhibit swarming as well. For example, in the classic predator-prey problem, the predator agents naturally “swarm” around the prey while surrounding it from all sides of the world. Therefore, even the limited sensory abilities of the agents in these systems would suffice to allow their cooperation through collective (e.g., surrounding) behavior. Conversely, in the WCP, the escape of caribou from a single wolf would naturally tend to disperse the caribou radially – a behavior that would somehow impede, or, even contradict the desired grouping (swarming) of these agents. Thus, the eventual survival value (if any) of swarming behavior of caribou agents in WCP is not as evident as in most other commonly considered artificial societies.

1.5. Methodology

The methodological holism of the proposed approach of applying GP implies that we can evaluate the quality of the evolved (lower level) behavior of the caribou agents from the higher-level features of the whole team, namely from the ability to escape from the chasing wolf. On the other hand, the heuristics of the proposed approach indicate that in order to develop the escape behavior of the caribou agents, we must rely on simulated evolution as a variant of an automated trial-and-error-correcting approach rather than on formal models of the properties of agents and their environment. Compared to the work of Tian, Tanev, and Shimohara[1][2], in our current research we propose a more plausible model for energy consumption by caribou agents. Moreover, we investigated the resulting emergent escape behavior of the team of caribou agents as well as the survival value of the size of the team of caribou agents.

1.6. Thesis Outline

The remainder of the article is organized as follows: in Section 2 we define the WCP and present the proposed abstract architecture of caribou agents. In Section 3 we introduce some background of genetic programming. In Section 4 we elaborate on the evolutionary framework and simulation framework. From section 5 to section 10, we implement different socio-psychological aspects to caribou agents, and investigate how the aspects influence to the efficiency of evolution or to the behavioral effectiveness. Finally, Section 11 draws a conclusion to our research.

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Basic Model of Wolf-Caribou Pursuit Problem

2. 1. Related Research

The origin version of the predator-prey pursuit problem was introduced by Benda *et al.*, And consisted of four predator agents trying to capture a prey agent by surrounding it from four directions on a grid-world. Agent movements were limited to either a horizontal or a vertical step per time unit. The movement of the prey agent was random and no two agents were allowed to occupy the same location. This version of predator-prey pursuit problem was called “orthogonal game” [25].

Gasser *et al.*, approached this problem by allowing the predators to occupy and maintain what is called a *lieb configuration* while homing in on the prey. This study did not provide any experimental results. Hence, their research was difficult to compare with other works [25].

Korf developed several greedy solutions to problems where eight predators are allowed to move orthogonally as well as diagonally. He calls this “diagonal game” [25].

The WCP we employed in our research, can be viewed as a reversed instance of modern predator-prey pursuit problem, which was originally defined and investigated by Tian, Tanev, and Shimohara[1][2].

2. 2. Wolf-Caribou Pursuit Problem (WCP)

2. 2. 1. Definition of Predator-Prey Pursuit Problem

The predator-prey pursuit problem involves multiple predator agents trying to capture a prey agent by surrounding it. This domain has many different instantiations that can be used to illustrate different multi-agent scenarios[8].

Predator-prey pursuit problem investigates the attack strategies, such as surrounding and chasing. On the contrary, WCP which we will elaborate later investigates the defense strategies, such as exhausting and distracting.

It is a realistic simulation system because the similar behaviors were found in real world by Karsten Heuer, a wildlife biologist in 2003, when he and his wife, Leanne Allison, followed the vast Porcupine caribou herb. Travelling more than a thousand miles with the animals, they documented a classic swarm defense of caribou agents[20].

They documented that, when the wolf started chasing, the nearest caribou turned and ran, and that response moved like a wave through the entire herd until they were all running. Reaction times shift into another realm. Animals closest to the wolf at the back end of the herb looked like a blanket unravelling and tattering, which, from the wolf's perspective, must have been extremely confusing. The wolf chased one caribou after another, losing ground with each change of target. In the end, the herd escaped over the ridge, and the wolf was left panting and gulping snow[20].

In this swarm defense documented by Karsten and Leanne, we can conclude that every caribou knew when it was time to turn, even if it did not know exactly why. WCP is proposed by employing this result, and we can know that the emergent behaviors simulated in WCP are realistic and may appear in real world.

2. 2. 2. Definition of Wolf-Caribou Pursuit Problem (WCP)

The employed instance of the WCP is an instance of a heterogeneous MAS featuring two types of agents – one *superior* wolf agent and multiple *inferior* caribou agents that must escape from the chasing wolf. In other words, the task of the wolf agent is to capture at least one caribou during the limited number of time steps of the trial. The task of the team of caribou is to prevent this from happening.

In our work, we consider an instance of the problem, which is more realistic than the commonly investigated problems in the past, via proposing a more plausible model for energy consumption by agents.

The task of the caribou agents is inherently cooperative in that they cannot escape from the wolf unless they cooperate with each other. Indeed, the wolf is superior to the caribou in terms of sensory abilities (range of sensors), raw speed, and energy. An eventual unhindered chase of a single caribou would inevitably result in a capture of the caribou. Conversely, an eventual cooperative behavior of caribou agent would result in a longer and, therefore, sub-optimal zigzag chasing trajectory, which, in turn would yield a higher rates of energy depletion of the wolf. Moreover, such cooperative behavior of caribou agent might exhibit an alternation of the currently chased caribou, where a stronger caribou attracts the attention of the wolf away from the already exhausted one.

2. 2. 3. Advancements of WCP

Although predator-prey pursuit problem is a well-studied and wild-used research tool for investigating the collective intelligence and emergent behaviors through interactions and communications between agents. Nevertheless, considering our objective is to verify the survive value of socio-psychological aspects, and in predator-prey pursuit problem social behaviors emerged anyway because their task is to capture prey by surrounding it. Namely, during the simulation, the predators will become a swarm and interact with each other inevitably. As a result, we employed WCP in this work.

Different from the predator-prey pursuit problem, in WCP, caribou agents will break the swarm naturally due to their escaping behavior. In other word, when and only when the implemented socio-psychological aspects have survived values, the corresponding social behaviors will be emerged.

To sum up, the predator-prey pursuit problem works better to investigate the attack strategies. But WCP is better to investigate defense strategies and verify whether some aspects help prey to survive which is the most suitable research tool for our work.

2. 3. Simulated World

As we mentioned above, the employed instance of the WCP was comprised of two types of agents: a single predator wolf agent and multiple caribou agents.

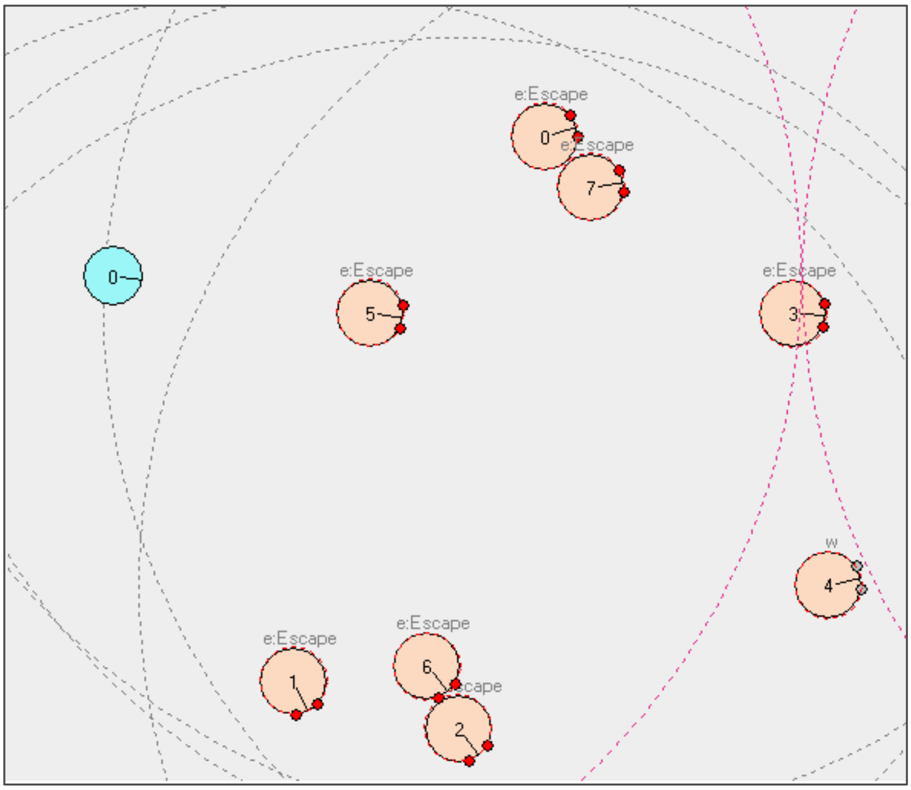

Figure 1 wolf-caribou predator-prey pursuit problem

Figure 1 illustrates a sample snapshot of the proposed WCP, comprising multiple caribou agents and a single wolf (shown in the top left part of the world). Various information, pertinent to each of the entities (such as position, heading, currently executed behavior, etc.) is displayed in real time during the simulation of the WCP. The dashed circles around the entities correspond to the visible range of their sensors. We model the world as a two-dimensional continuous (infinite) torus visualized as a 2D-surface which is widely-used and relatively easy to implemented[3].

2. 4. Architecture of the Caribou Agents

We adopt a purely reactive, subsumption architecture of the caribou agents in which the functional modules are distributed in three “levels of competence” for the overall behavior of caribou agents: wandering (lowest priority), escaping from wolf, and social behavior (highest priority) – coordinated movements aimed at distracting or deceiving the chasing wolf (Figure 2).

The moving abilities of caribou agents are continuous; they can turn a numeral angle from their current heading. But the speed is discrete, an agent can run at speeds equal to one of some decided percentage of its maximum speed. Furthermore, caribou agents feature a gradual decrease in their energy level. The energy decreases linearly with the increase of the overall distance travelled by the agents since the beginning of the trial.

The basic perceptions of caribou agents are based on the proximity perception model, they can see both peer agent and wolf agent. The visual field of the sensors of caribou agent is 360 degrees[4].

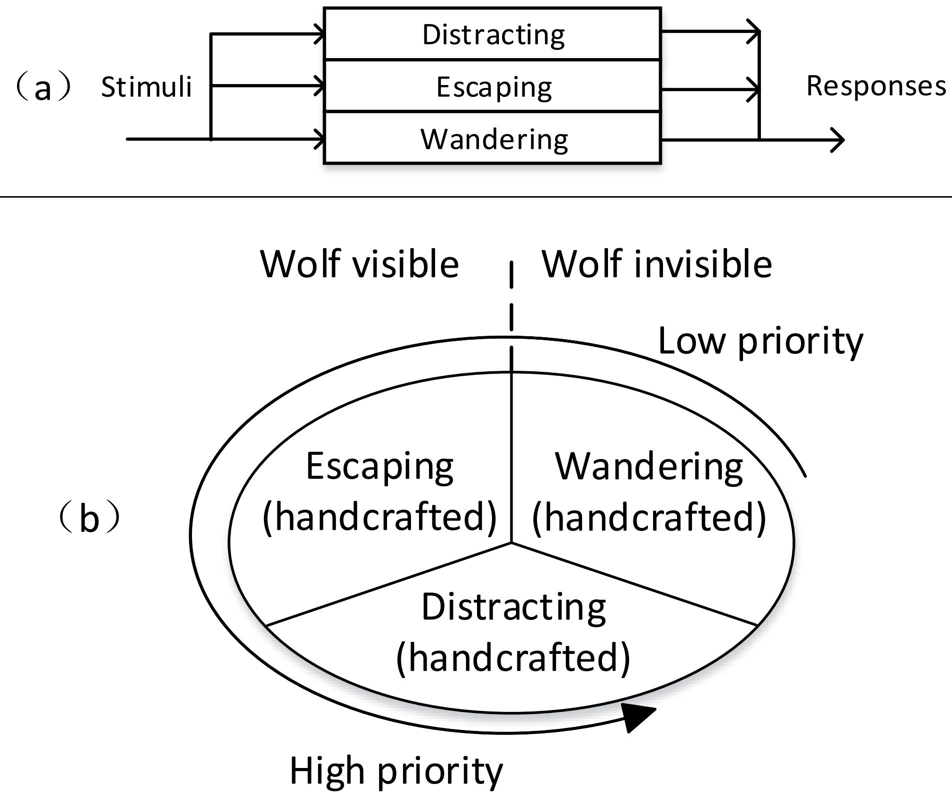

Figure 2 Subsumption architecture of caribou agents (a) their respective inter-state transition model (b)

2. 5. Summary

In this chapter, we introduced: i) the related works about predator-prey pursuit problem and WCP, ii) the definition of predator-prey pursuit problem and WCP. Afterwards, we introduced why Tian *et al*. proposed WCP - the advancement of WCP and the documented situations in real world. Finally, we introduced the architecture of two types of agents: a *superior* wolf agent and multiple *inferior* caribou agents.

We mentioned that we employed GP as the solution-search tool in this work, hence, in chapter 3, we will introduce some basic concepts of GP.

2. 6. References

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Basic Concepts of Genetic Programming

3. 1. Introduction

Genetic programming (GP) is an evolutionary computation (EC) technique that automatically solves a problem without requiring a user to know or specify the form or structure of the solution in advance. In other words, GP is a heuristic solution-search or optimization technique. At the most abstract level GP is a systematic, domain-independent method for getting computers to solve problems automatically starting from a high-level statement of what needs to be done[11].

3. 2. Genetic Representation

In GP, programmings are usually expressed as *syntax trees* rather than as lines of code. In more advanced forms of GP, programs can be composed of multiple components (e.g., subroutines). In this case the representation used in GP is a set of trees (one for each component) grouped together under a special root node that acts as glue[11].

3. 3. Selection

As with most evolutionary algorithms, genetic operators in GP are applied to individuals that are probabilistically selected base on fitness. That is, better individuals are more likely to have more children programs than inferior individuals. The most commonly employed method for selecting individuals in GP is tournament selection, in which a number of individuals are chosen at random from the population. The chosen individuals are compared with each other and the best of them is chosen to be the parent[11].

3. 4. Crossover and Mutation

GP departs significantly from other evolutionary algorithms in the implementation of the operators of crossover and mutation. The most commonly used form of crossover is *sub-tree crossover*. Given two parents, sub-tree crossover randomly and independently selects a *crossover point* (a node) in each parent tree. Then, it creates the offspring by replacing the sub-tree rooted at the crossover point in *copy* of the first parent with a *copy* of the sub-tree rooted at the crossover point in the second parent.

The most commonly used form of mutation in GP (is called *sub-tree mutation*) randomly selects a mutation point in a tree and substitutes the sub-tree rooted there with a randomly generated sub-tree[11].

3. 5. Summary

In this chapter, we introduced basic concepts of genetic programming which is employed in this work as the solution-search tool. We introduced the representation used in GP. Furthermore, we introduced the most commonly genetic operators used in GP: tournament selection, sub-tree crossover and sub-tree mutations. In chapter 4, we will elaborate the two frameworks employed in this research: i) simulation framework -- SimBoard, ii) evolutionary framework -- XGP Manager.

3. 6. References

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Research Framework for Hypothesis Testing

4.1. Simulation Framework – Simulated Board

4.1.1. Implementation of Simulated World

As we mentioned in chapter 2, we model the world as a two-dimensional continuous (infinite) torus visualized as a 2D-surface with simulated (scaled down) dimensions 1800m×1800m. In other words, if any agent is out of the right border, it will appear from the left border, and vice versa. On the vertical axis is same, if one agent is out of the top border, it will appear from the bottom border, and vice versa. Although this is a very simple model and there are lot of other choices, however, we employed this model considering that our focus is to investigate the survive value of different socio-psychological aspects.

4. 1. 2. Implementation of Caribou Agents

As we introduced, the functional modules of caribou agents are distributed in three "levels of competence": random wandering (lowest priority), escaping from wolf, and social behavior (highest priority) as shown in Figure 2.

In all of them, the random wandering and escaping are straightforward behaviors, and we handcrafted them in the functionalities of the caribou agents. However, social behavior of each caribou agent is the type of behavior that actually accounts for the behavior of other entities, and consequently, contributes to the emergence of the higher (team-) level escaping behavior. Due to the enormous complexity of the relationship between the entity-level and the team-level properties of WCP, we propose an approach that employs GP for the evolution of the social behavior of the caribou agents. Details of the evolutionary framework are elaborated below.

We mentioned that the speed of agents is discrete, therefore, in the work, the caribou agents can run at speeds equal to 0, 0.25, 0.5, 0.75 and 1.0 of their maximum speed which will influenced by its energy level. As a basic model of caribou agent, it can only see (i) the closest peer agent, and (ii) the wolf, and only if these are within the limited range of visibility of their simulated sensors. We will implement additional perceptions for different experiments.

4. 1. 3. **Implementation of Wolf Agents**

We elaborated the architecture of caribou agent detailed, by contrast, we did not mention the architecture of wolf agent. That is because we adopt a very simple wolf model in which the wolf only i) can see and chase the closest caribou if the caribou is within the limited visibility range, ii) runs at its maximum speed when chasing the caribou agent. Hence, we implemented the behavior of the wolf agent by handcrafted, as the wolf always chases the closest caribou agent. We consider such a simple, yet reasonably realistic behavior of the wolf as the first step towards the future development of a WCP in which the behaviors of both the wolf and caribou would be allowed to co-evolve.

As the same as caribou agents, the energy also implemented on wolf agent with higher initial energy. Owing to this feature, caribou agents are able to exhaust the wolf agent and to survive.

Table 1 illustrates the main parameters of the wolf and caribou agents.

Table 1 Main parameters of wolf and caribou agents

Parameter	**Wolf**	**Caribou**
Number	1	8
Range of sensors	900 m	660 m
Visual field of sensors	Omnidirectional, 360°	Omnidirectional, 360°
Max speed	19 m/s	17 m/s
Initial energy	150 units	100 units

4. 2. Evolutionary Framework - XGP Manager

4. 2. 1. Representation of Evolved Genetic Programs

We modelled the behavior of caribou agents as an evolvable set of stimulus-response behavior rules. In principle, such a behavior of caribou agents can be developed using various nature-inspired techniques, including genetic algorithms (GA), genetic programming (GP), and artificial neural networks (ANN).

However, considering we try to evolve the escaping strategy (represented as a program), GA is not suitable. Besides, the objective of this work is to investigate whether the socio-psychological aspects influence the evolution, therefore, black box technique such as ANN is not suitable. Consequently, we employed GP in this work.

Furthermore, motivated by the expressiveness, flexibility, and wide-spread adoption of the extensible markup language (XML) and document object model (DOM), we employed the XML-based genetic programming framework (XGP), in which the evolved genetic programs are represented as DOM-parse trees with corresponding flat XML-texts[12].

XGP is a domain-independent problem-solving approach in which a population of individuals (encoded as computer programs) evolves – by means of modelling the Darwinian principle of reproduction and survival of the fittest – to solve various design-, control- and optimization problems. In XGP, the genetic programs (individuals) are typically represented as parse trees whose nodes are functions, variables, or constants.

Nodes that are the roots of sub-trees are non-terminal and they represent functions. The sub-trees of the functional nodes correspond to the arguments of the function of that node. Both the variables and the constants are terminals; they do not require arguments and they always are leaves in the parse tree. The set of terminals includes the perceptions (stimuli) and actions (responses) that the caribou is able to sense and perform, respectively. The function set consists of arithmetical and comparison operators as well as logical IF-THEN rules (functions) that map certain stimuli into the corresponding response(s). Table 2 shows the set of benchmark functions and benchmark terminals of the proposed GP used to evolve the escape behavior of caribou agents. The main attributes of GP – genetic representation, genetic operations, breeding strategy, and a fitness function are elaborated in the following subsections.

Table 2 Sets of functions and terminals of GP used to evolve the escaping behavior of caribou agents

Category		**Designation**	**Explanation**
Set of Functions		IF-THEN, LE, GE, WI, EQ, NE, +, -	IF-THEN, ≤, ≥, Within, =, ≠, +, -
Set of Terminals	**Sensory abilities**	Wolf_d	Distance to the wolf
		Wolf_a	Bearing (angle in the visual field) of the wolf
		Peer_d	Distance to the closest caribou
		Peer_a	Bearing (angle in the visual field) of the closest caribou
		Chased_Peer_d*	Distance to the chased caribou
		Chased_Peer_a*	Bearing (angle in the visual field) of the chased caribou
		Chased	*True* if caribou is the one being chased, *False* otherwise
	State variable	Speed	Speed of the agents (m/s)
		FasterThanChased*	*True* if own speed is higher than that of the caribou being chased, *False* otherwise
	Ephemeral constant	Integer	Random value within [0…10]
	Moving abilities	Turn(α)	Turns from the current orientation to α degrees (α>0 means clockwise)
		Stop, Go_1.0	Stops the caribou or sets the speed to max value.
		Go_0.25, Go_0.5, Go_0.75	Sets speed to 0.25, 0.5, and 0.75 of maximum

4. 2. 2. Genetic Operations: Selection, Crossover, and Mutation

As a selection mechanism, we use a binary tournament selection, which has been demonstrated to be both simple to code and computationally efficient. We implemented a strongly typed crossover in that only the nodes (with the corresponding subtrees) of the same data type (i.e. labelled with the same XML-tag) from the selected parents can be swapped. The random sub-tree mutation is also implemented in a strongly typed way where a random node can be replaced only by a randomly created syntactically correct sub-tree. The mutation operation checks the type of modified node and applies a randomly chosen syntax rule from the set of applicable rules as defined in the grammar of XGP[3][4].

4. 2. 3. Breeding Strategy

The breeding strategy (applied to the evolved caribou agents only) is homogeneous, in that a single genetic program is cloned to all caribou agents. The fitness of the genetic program is calculated from the behavior of the whole team of caribou agents during the fitness trial, as detailed below.

The reasons for employing homogeneous caribou agents are that the search space of genetic programming is smaller, and therefore – the optimal solutions could be obtained more efficiently. Moreover, even the heterogeneous animals (and humans too) share the same "universal values" (with empathy, among them) due to their importance for the survival of species. This allows us to approximate these, naturally heterogeneous systems, as homogeneous ones.

In our future work we are planning to implement the heterogeneity of caribou agents, e.g., by considering different values of their initial energy levels, different range of their sensors, and – ultimately – different sets of IF-THEN behavioral rules behaviors – to model children-, adult-, and elderly caribous. Consequently, interesting escaping strategies of protecting the weak caribou from the chased wolf could emerge.

4. 2. 4. **Fitness Function**

To obtain the general escape behavior of the caribou agents, the fitness of each genetic program was evaluated as an average of the fitness values obtained from 10 different initial situations. In each of these initial situations, the caribou agents were positioned at random distances at least 60m from the centre of the world and the wolf was placed at a random position in the world with a random orientation at a distance between 300 m and 500 m from the closest caribou agent. With these initial conditions, several caribou agents are visible to the wolf, but none are close enough to be captured immediately.

The fitness value calculated for each of these initial situations consists of the following two components:

- The time needed for the wolf to capture a caribou. A higher value corresponds to a better-performing team of caribou agents. The maximum (i.e., best possible) value of this component is equal to the maximum number of the time steps of the trial (i.e., 600).
- "Parsimony pressure" is introduced with the intention to reduce the "bloat" in GP by penalizing the fitness of excessively complex (i.e., featuring too many tree nodes) genetic programs. In our approach, we calculate the penalty as the number of tree nodes divided by 50. Therefore, the fitness of a genetic program featuring, say, 1000 tree nodes would be penalized (i.e., reduced) by a value of 1000/50=20.

With the fitness function, as defined above, the team of caribou agents was implicitly rewarded for escaping the wolf rather than for exhibiting particular traits of the eventual escaping behaviors. The fitness value reflects what, rather than how the team of caribou agents achieves. The escape behavior, which is "invented" during the simulated evolution, should emerge from the relatively simply defined perception and moving abilities of the caribou agents. Table 3 shows the main parameters of the proposed GP.

Table 3 Main parameters of GP

Parameter	**Value**
Population size	400
Selection mechanism	Binary tournament
Selection rate	10%
Mutation mechanism	Random subtree mutation
Mutation rate	5%
Elitism	4 Individuals
Fitness trial	Over 600 time steps, for 10 different initial situations
Fitness value	Average over all 10 initial situations of the (i) time needed for the wolf to capture a caribou (ii) decreased by the "parsimony pressure" factor
Termination criteria	((Fitness=600) AND (Successful situations=10)) OR (No fitness improvements for 60 generations)

4. 2. 5. Termination Criteria

Based on empirically proven data that in the initial stages of evolution, the caribou agents are hardly able to successfully find solutions more than a few (out of 10) initial situations of position and orientation of entities. In order to enhance the computational performance of the evolution, we implemented a noisy evaluation of the fitness function as follows. With the start of each evolutionary run of GP, the evolved caribou agents are evaluated on just one initial situation. As soon as this initial situation is resolved (i.e., no single caribou is being captured by the wolf) within the designated duration of the trial (600 time steps), an additional (second) situation is added to the set of situations used for the evaluation of the escaping capabilities of the team of evolved caribou agents. The increment of the number of initial situations continues with the success of all currently considered initial situations until the number of successfully resolved situations reaches the number 10. This favorable outcome corresponds to a successful evolutionary run, i.e., a run that yields an evolved behavior of caribou agents that contributes to the successful escape of the team of caribou agents. In unfavorable evolutionary runs, we terminate the evolution if the caribou are unable to resolve the current set of initial situations within a reasonable number of generations (i.e., 60).

4. 3. Instance of WCP

The snapshots of WCP is shown in Figure 3, and we can find that the WCP consisting of two subsystems – GP Manager and Simulation Board (named as SimBoard).

The GP Manager which is shown in left of Figure 3, maintains the population of genetic programs and implements the genetic operations (selection, crossover, and mutation). On the other hand, the SimBoard which is shown in right of Figure 3, models the behavior of all entities during the trial, and evaluates the fitness value of the team of caribou agents. The two components can communicate each other in many ways, e.g., by UPD or by DCOM.

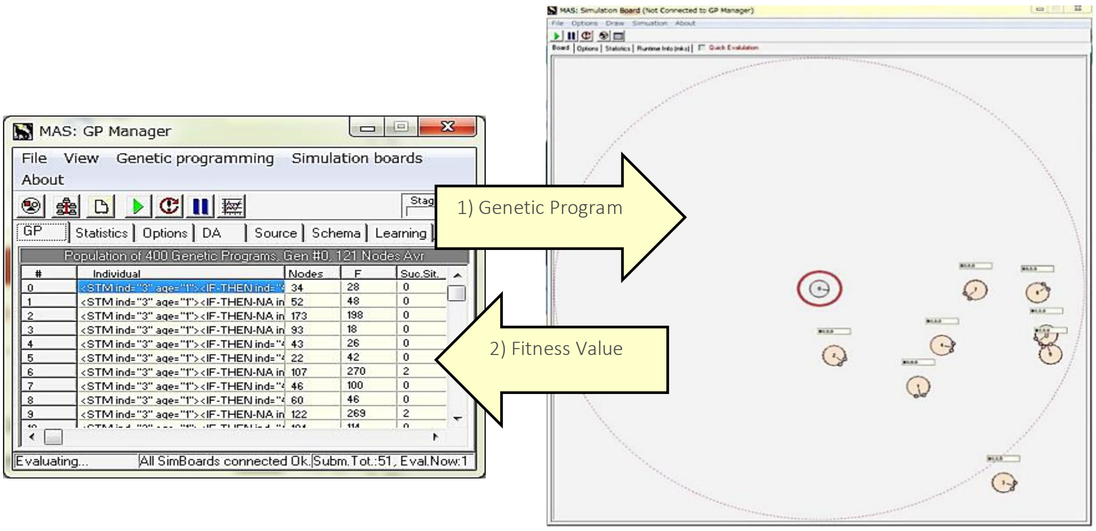

Figure 3 Snapshots of WCP

In this chapter, we introduced two frameworks employed in this work: i) simulation framework -- SimBoard and ii) evolutionary framework -- XGP manager. Moreover, we detailed how we implemented i) the simulated world, ii) the caribou agent and iii) the wolf agent. Finally, we i) explained the reason why we employed GP, ii) introduced the XGP which is the instance of GP we used in this work and the implementation of genetic operators of XGP, and iii) elaborated the benchmark evolution parameters we used in this work. From the next chapter, we will start to introduce our experiments and experimental results.

Firstly, in Chapter 4, we will elaborate the experiment we constructed to investigate our first interested socio-psychological aspects -- empathy, and explain the experimental results.

4. 4. References

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Charpter-5

Verifying the Survival Value of Empathy

5.1. Introduction

The WCP is defined to be inherently cooperative in that the inferior caribou agents are unable to escape from the superior wolf unless they cooperate with each other. In order to achieve this, we implemented empathy to make the caribou agents able to see the chased caribou and know the chased caribou agent needs help. We explicitly expected empathy can solve the WCP problem and try to proof it experimentally.

Moreover, we modeled energy in both caribou agents and wolf agent to obtain a more realistic WCP problem, hence, we verified how the energy level influenced the evolution.

5. 2. Definition of Empathy

From the point of view of psychology, empathy has many definitions that encompass a broad range of emotional states, including experiencing emotions that match another person's emotions; discerning what another person is thinking or feeling; and making less distinct the differences between the self and the other. It can also be understood as having the separateness of defining oneself and another blur.

But in this research, we associated compassion and sympathy with empathy, therefore, our empathic agent will care for other peers and having a desire to help them.

5. 3. Experimental Setting

5. 3. 1. Experimental Setting of WCP with Empathic Caribou

We conducted additional 20 runs of XGP to evolve a successful escaping behavior of the team of 8 empathic caribou agents. We incorporated the empathy by introducing additional perceptions that allow the caribou agents to perceive the distance and bearing of the currently chased caribou (refer to Table 2). Notice that introduction of empathic perceptions does not automatically imply an emergence of compassionate behavior, i.e., that the caribou agents will use these perceptions in order to help the chased peer. The compassionate behavior should be eventually discovered by the simulated evolution providing that such a behavior brings a certain survival value to the team of caribou agents.

5. 3. 2. Experimental Setting of WCP with Non-empathic Caribou

As the comparison experiment we conducted another 20 independent runs of XGP in an attempt to evolve a successful escaping behavior of the team of 8 caribou agents *without empathy*. Within the considered context of the WCP we view the empathy as the ability of the caribou that are not currently chased by the wolf to understand and share the feelings of the chased one. Without incorporating any empathy, the perceptions of caribou agents include the distance, bearing of the wolf, and the closest peer (as indicated in Table 2).

5. 4. Experimental Results

5. 4. 1. Experimental Results of WCP with Non-empathic Caribou

The dynamics of the number of successful situations for these runs is shown in Figure 4. As Figure 4 illustrates, in none of the 20 runs of GP the team of caribou agents is able to escape in all 10 initial situations. In average (shown as dashed line in Figure 4), the team of caribou agents escapes only in about 2 (of 10) initial situations.

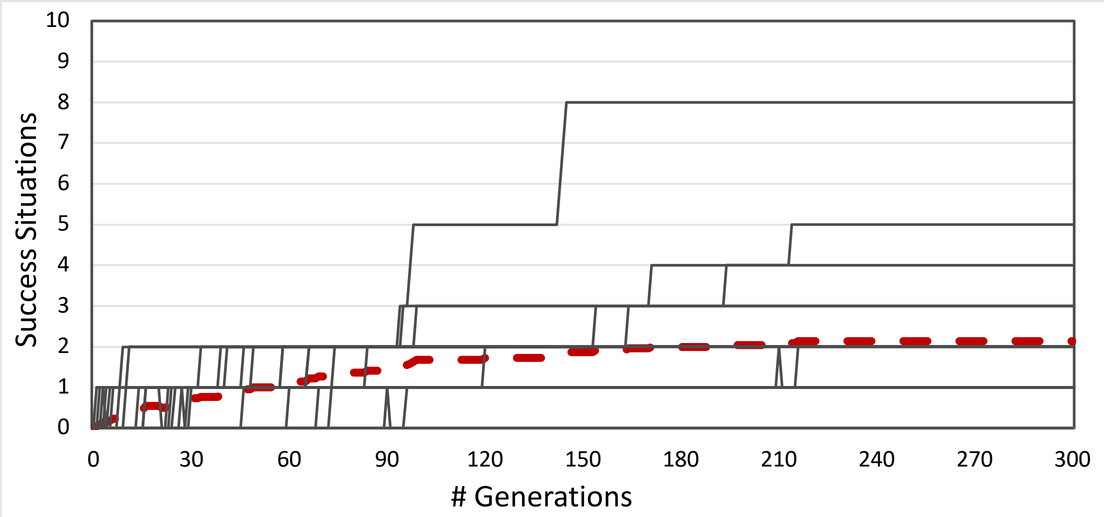

Figure 4 Dynamics of the number of successful situations for 20 independent runs of GP evolving a team of 8 caribou agents without empathy. The maximum number of initial situations is 10, and in none of the 20 runs of GP the team of caribou is able to escape in all 10 initial situations. In average (shown as dashed line), the team escapes in about 2 (of 10) initial situations

5. 4. 2. Experimental Results of WCP with Empathic Caribou

The dynamics of the number of successful situations for 20 runs of GP evolving a team of 8 empathic caribou agents is shown in Figure 5. As Figure 5 illustrates, the maximum number of initial situations is 10, and in 17 out of 20 runs (i.e., in 85% of runs) the team of empathic caribou is able to escape in all 10 initial situations. In average (shown as dashed line in Figure 5), the team escapes in about 9 (of 10) initial situations.

The obtained results suggest that with emphatic agents, the evolution is both more efficient (i.e., the same number of successful situations are attained faster than in the team of non-emphatic caribou) and the emerged escaping behavior is more effective.

The average number of successful situations is much higher – 9 vs. 2 – than in the team of non-emphatic caribou.

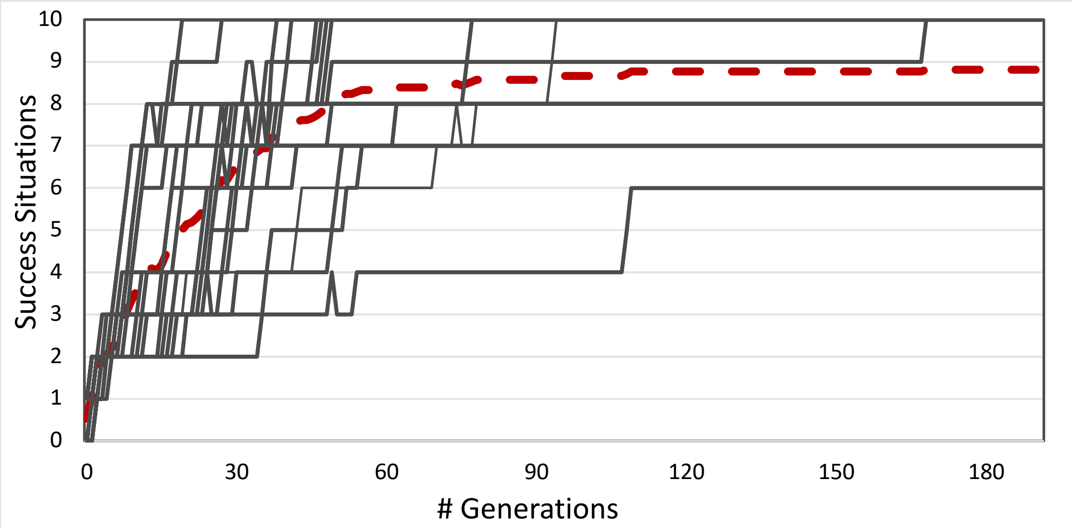

Figure 5 Dynamics of the number of successful situations for 20 independent runs of GP evolving a team of 8 empathic caribou agents. The maximum number of initial situations is 10, and in 17 out of 20 runs of GP the team of caribou is able to escape in all 10 initial situations. In average (shown as dashed line), the team escapes in about 9 (of 10) initial situations

5. 4. 3. Comparison of WCP with Empathic and Non-emphatic Caribou

We obtained both the experimental results from with empathy and without empathy, and compared them. Figure 6 shows the dynamics of the average number of successful situations for 20 runs of GP evolving a team of eight caribou agents with and without empathy behavior. Figure 7 shows the results of statistical analysis using analysis of variance (ANOVA).

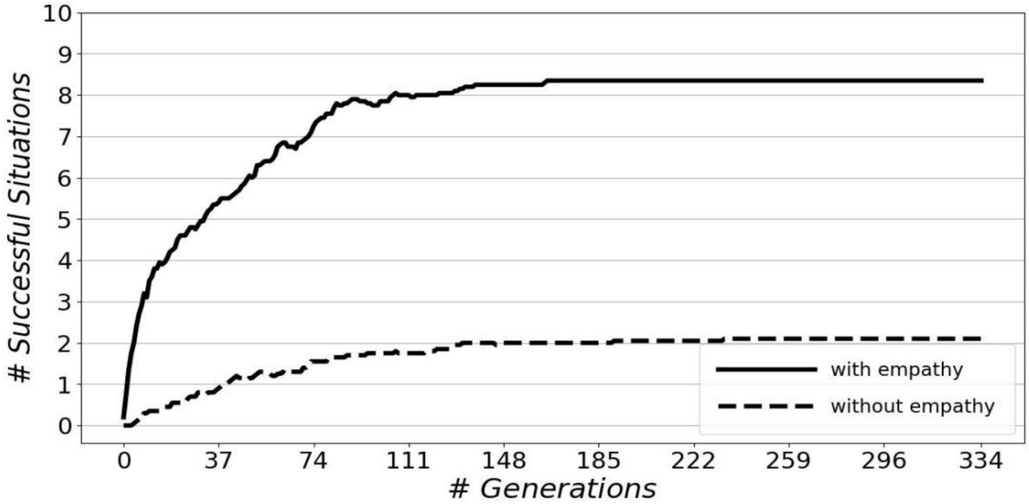

Figure 6 Dynamics of the average number of successful situations for 20 runs of GP evolving a team of eight caribou agents with and without empathy behavior

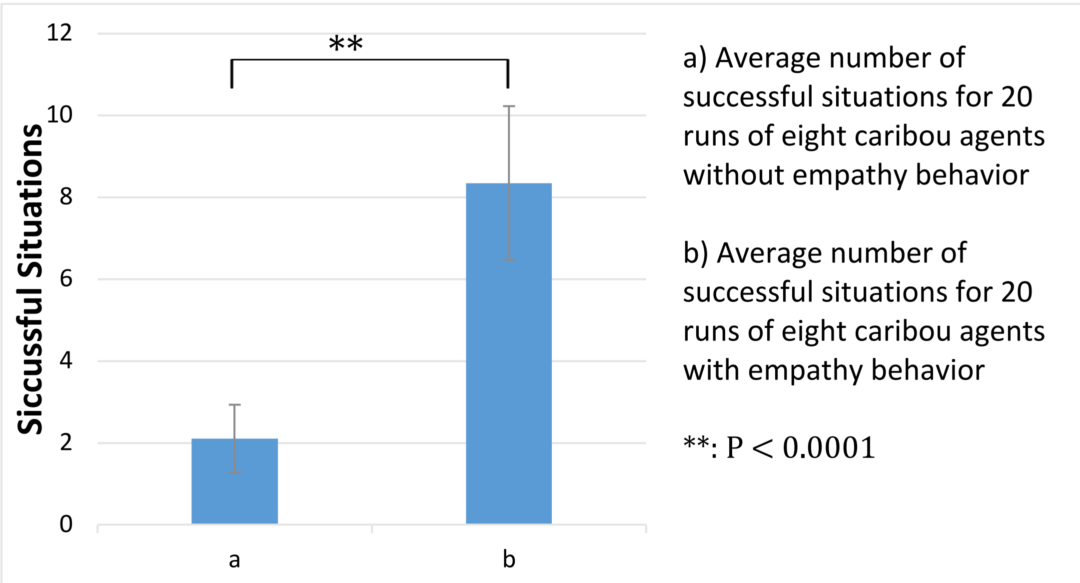

Figure 7 Experimental results of ANOVA test

5. 4. 4. Consumption of Energy by Wolf and Caribou Agents

In order to investigate the dynamics of the energy consumption by wolf and caribou agents in both cases (caribou agents without- and with empathy) we plotted the energy level of entities at each instant of two sample trials: (i) an unsuccessful situation for a team of caribou agents without empathy (Figure 8) and (ii) a successful escape of a team of empathic caribou agents (Figure 9). As the figures illustrate, by the time the caribou of non-empathic team is captured (around time step #371 shown in Figure 8) the wolf features significant energy superiority over all caribou agents. In contrast, at the same time (time step #371, Figure 9) the wolf enjoys relatively insignificant superiority over the energy levels of some of the empathic caribou agents. We speculate that the reduced energy superiority of the wolf over (at least) some of caribou agents are relevant for the success of their escaping behavior.

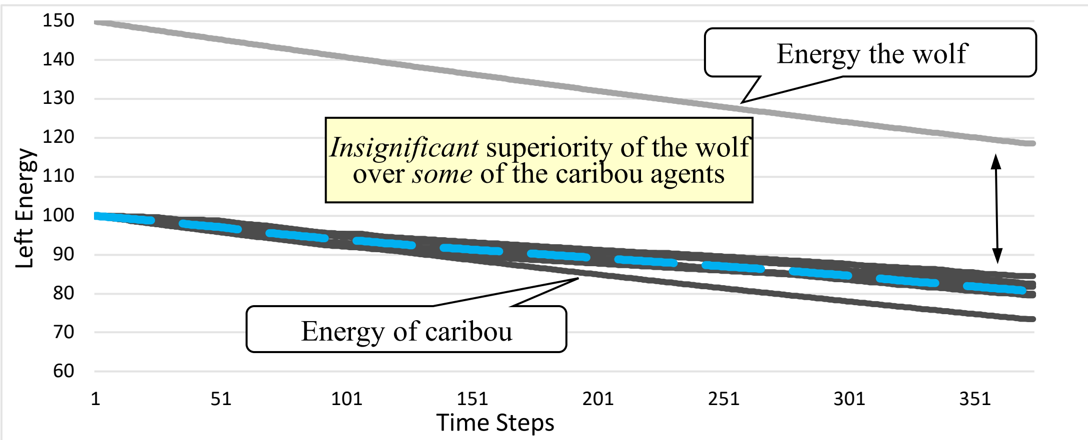

Figure 8 Dynamics of the energy levels of all agents with caribou without empathy during a sample unsuccessful (i.e., a caribou agent is caught at time step #371) trial. Dashed line represents the average energy of all caribou agents

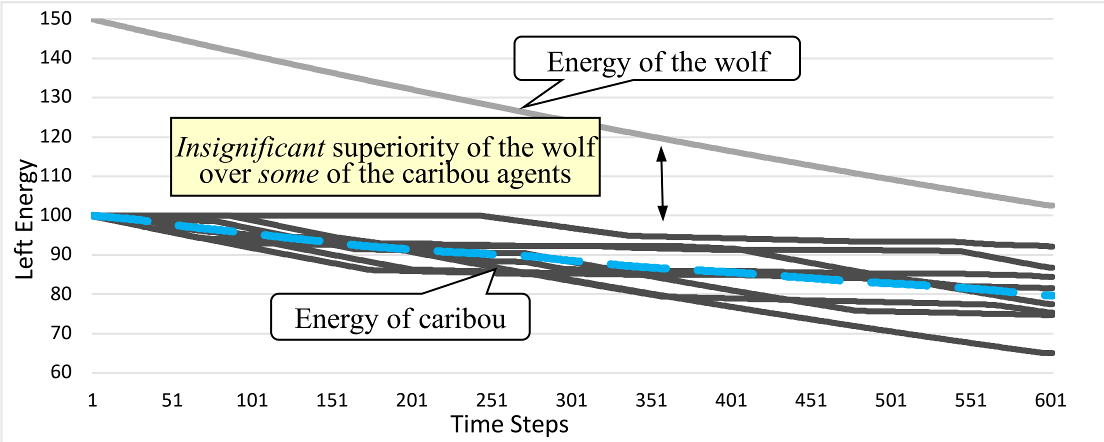

Figure 9 Dynamics of the energy levels of the agents with empathic caribou during a sample successful trial (i.e., wolf is unable to catch any caribou by the end of the trial at time step #600). Dashed line represents the average energy of all caribou agents

5. 5. Emergent Escaping Behavior of the Team of Empathic Caribou Agents

A sample emergent escaping behavior of the team of empathic caribou agents is shown in Figure 10. The behavior exhibits the following strategy:

- A compassionate Caribou #i spares its own energy by moving slowly towards the escaping path of the chased Caribou #j.
- As Caribou #j approaches Caribou #i, the latter stops moving in order to expose itself closely to the chasing wolf.

The wolf switches its attention from the exhausted Caribou #j to the currently closest (yet, energetically fresher) Caribou #i which allows the Caribou #j to escape.

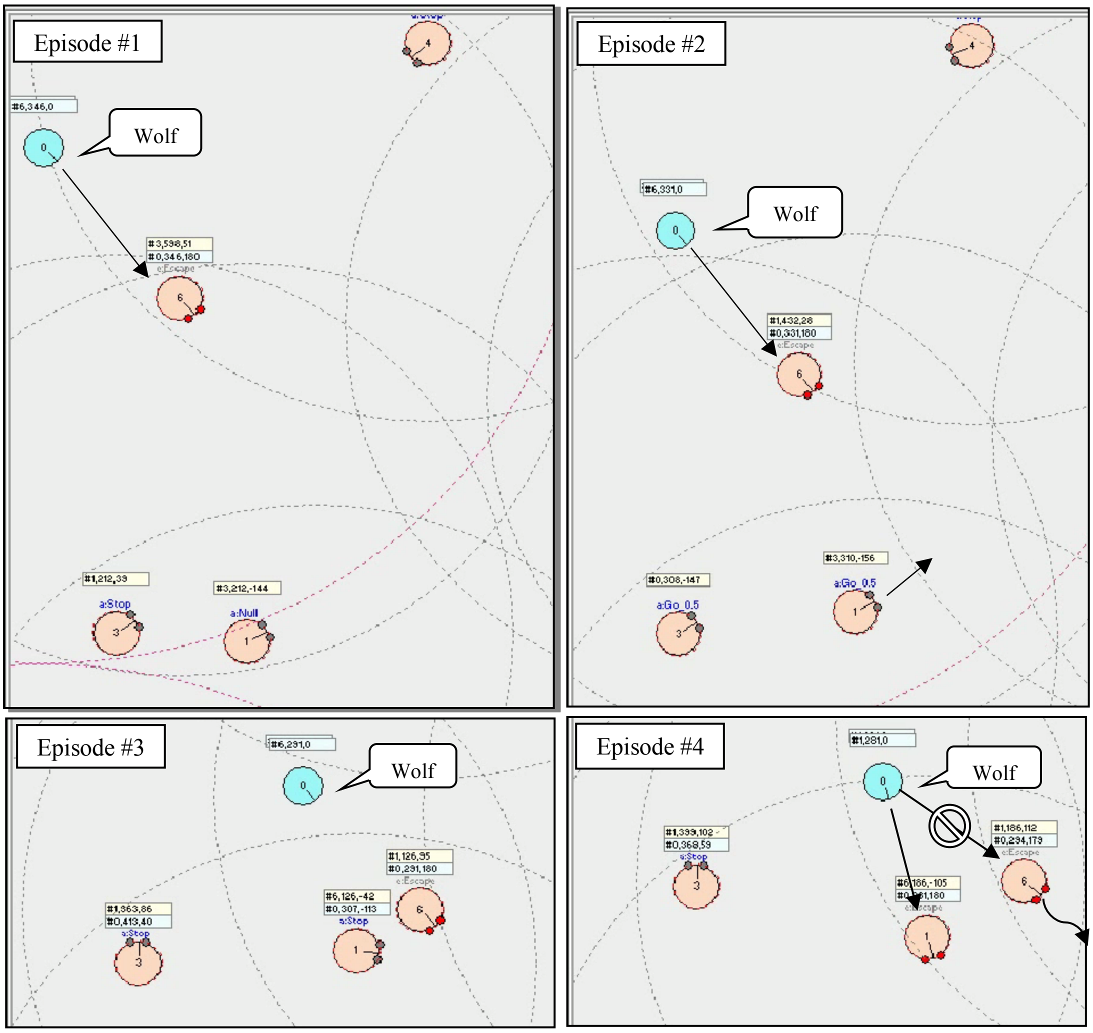

Figure 10 Emerged compassionate behavior by automatically evolved empathic caribou agents: as the wolf chases Caribou #6, Caribou #1 saves energy by moving slowly towards the escaping path of the chased Caribou #6 (Episodes #1 and #2). As the Caribou #6 approaches Caribou #1, the latter stops moving in order to expose itself as the closest to the chasing wolf (Episode #3). The wolf switches its attention from the exhausted Caribou #6 to the currently closest (yet, energetically fresher) Caribou #1 (Episode #4) which allows the Caribou #6 to escape

5. 6. Conclusion and Discussion

5. 6. 1. Conclusion

We demonstrated the feasibility of evolving (via genetic programming) the escaping strategies of a team of caribou agents in the wolf-caribou predator prey problem (WCP). The WCP comprises a team of eight caribou agents that is required to escape from a single yet superior wolf agent in a simulated two-dimensional toroidal world. We experimentally proved the survival value of empathy in that its incorporation in caribou agents significantly improves both the efficiency of the behavioral evolution and the behavioral effectiveness. Moreover, because a single caribou could never escape from the superior wolf, the very ability of the team of empathic caribou agents to escape could also be seen as an illustration of the emergent nature of successful escaping behavior – in that the higher (team-) level properties are more than a mere sum of the properties of its individual entities.

5. 6. 2. Discussion

In this chapter, we experimentally verified that the emerged social behaviors make the caribou agents interact and communicate between each other, and improve the escaping strategies. Therefore, we are interested in investigating whether and how the group size of caribou agents influences the escaping strategies. We constructed an experiment to verify the survive value of the group size of empathic caribou agents. The detail information will be elaborated in the next chapter.

From the experimental results shown in this chapter3, we can verify that distracting behaviors, indeed, emerges in the evolved behaviors of caribou agents even without the implementation of empathy. However, this behavior is not very efficient. Because the non-empathic sense only the closest caribou, they could not sense the caribou that is currently chased by the wolf, and therefore, they could not adjust their behavior appropriately in order to help it. Occasionally, this closest caribou could be – just by chance – the chased one, and then the empathic behavior could, indeed, emerge. That is the reason why non-empathic caribou can resolve some situation (increased with the increase of density of population of caribou agents) but in most of the tested initial situations they fail.

Conversely, in the implementation of the empathic caribou, in addition to the perception of the closest caribou, we added other perceptions – the distance and the bearing of the chased caribou. These two parameters are used by GP as two additional terminal symbols, and using these additional terminals, the GP could evolve better, more efficient (empathic) IF-THEN set of behavioral rules – e.g., turning and moving towards the chased caribou in order to distract the wolf (especially if the caribou is also conscious that it has more energy than the chased one). Moreover, one of the challenges of this MAS is the radially escaping behavior of caribou would eventually break the swarm, but the implementation of empathy can facilitate the preservation of the swarm and, which also helps achieving a more efficient escaping strategy.

Charpter-6

Verifying the Survive Value of Team Size of Caribou Agents

6.1. Introduction

In the previous chapter, we experimentally verified that the interactions and communications between caribou agents improve both the efficiency of evolution of escape behavior and the effectiveness of such a behavior. Then, we are interested in whether the changes of the group size will influence the result of evolution. In other words, we are interested in verifying the survive value of group size and investigating how the group size influence the evolution.

From another viewpoint, the results may also be a demonstration of the transition of the quantity (team of eight inferior caribou agents) into quality (an ability to escape from the superior wolf).

In this chapter, we will introduce the experimental setting and elaborate the results of the experiments we conducted to investigate the role of the quantity in this transition in detail.

6. 2. Experimental Setting

In order to achieve this, we consider the evolution of the escaping behavior of various sized teams of caribou agents (e.g., one, two, four and six). We use the empathic caribou agents (caribou agents with empathy) in the comparison experiments, and the results with group size equal to 8 used as the benchmark (Figure 5). That is, the perception and moving abilities of the caribou agents are identical to the corresponding abilities of the previously considered team of eight caribou agents. Additionally, the main parameters of GP (population size, crossover, and mutation rate) are the same.

6. 3. Experimental Results

For all of the considered variably sized teams of caribou agents, we conducted 20 independent runs of GP. Figure 11, Figure 12, Figure 13 and Figure 14 show the results (the result of 8 caribou agents is same as the previous benchmark data which is shown in Figure 5). The experimental results of the evolution of the escaping behavior by a single caribou agent are not shown as the result is trivial; without an evolutionary run of GP, the inferior caribou is unable to escape from the superior wolf. This also suggests that the successful escape of eight caribou agents is, indeed, facilitated by the collective behavior exhibited by the team of caribou agents.

On the other hand, a team of *two* caribou agents is able to escape in one or two initial situations, and the average number of successful situations is 1.6 (Figure 11). Increasing the number of caribous somehow contributes to the overall success of the team's escaping behavior. Further increasing the number of caribous to *four* improves the chances of the caribou agents to successfully escape from the wolf even more. The average number of successful situations in still low – about 1.4 (from 10), but the maximum number of successful situations is six, which is a significant increase from the two successful situations by the team of two caribou agents (Figure 12).

The team of six caribou agents in several runs of GP achieves a successful escape in all 10 initial situations (Figure 13). The average number of successful situations (6.5) is also higher than those for the smaller teams of caribou agents, but is still lower than the average for the initially considered team of eight caribou agents.

However, when the caribou group size is too high (i.e., the population density of caribou is too high), both the efficiency of evolution and the behavioral effectiveness somehow deteriorate (Figure 14).

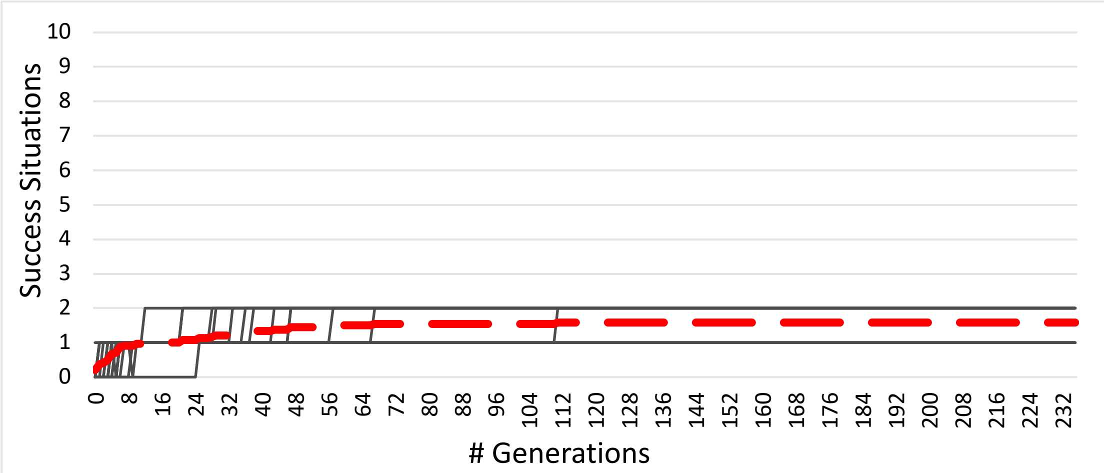

Figure 11 Dynamics of the number of successful situations for 20 independent runs of GP evolving the escaping behavior of a team of with 2 caribou agents

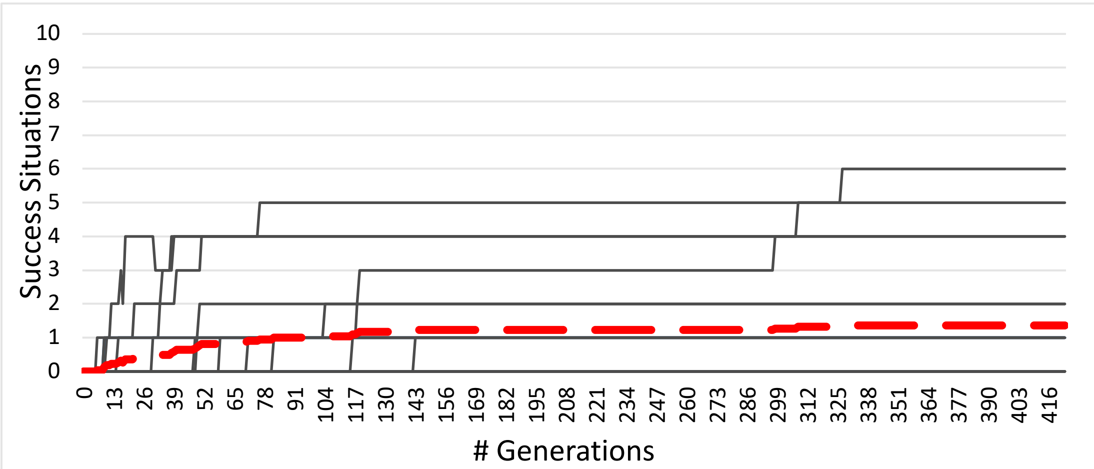

Figure 12 Dynamics of the number of successful situations for 20 independent runs of GP evolving the escaping behavior of a team of with 4 caribou agents

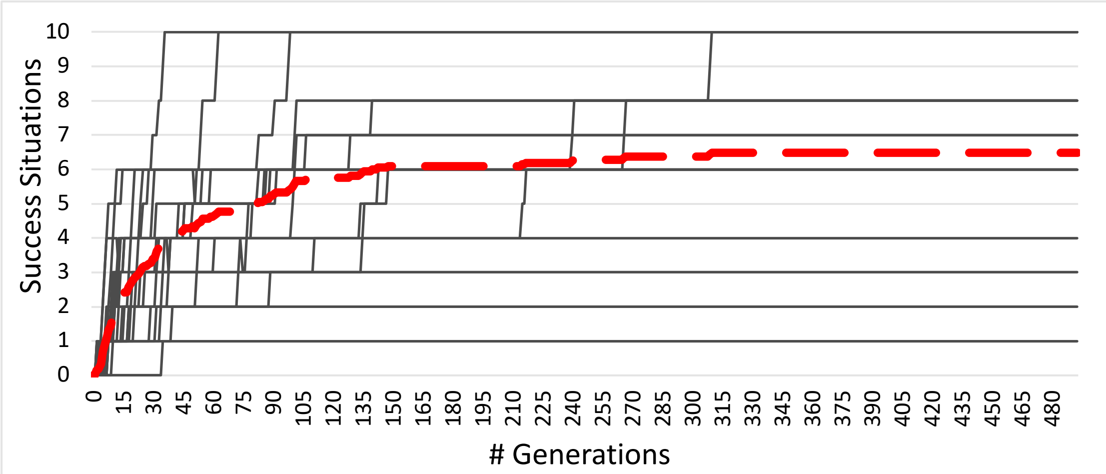

Figure 13 Dynamics of the number of successful situations for 20 independent runs of GP evolving the escaping behavior of a team of with 6 caribou agents

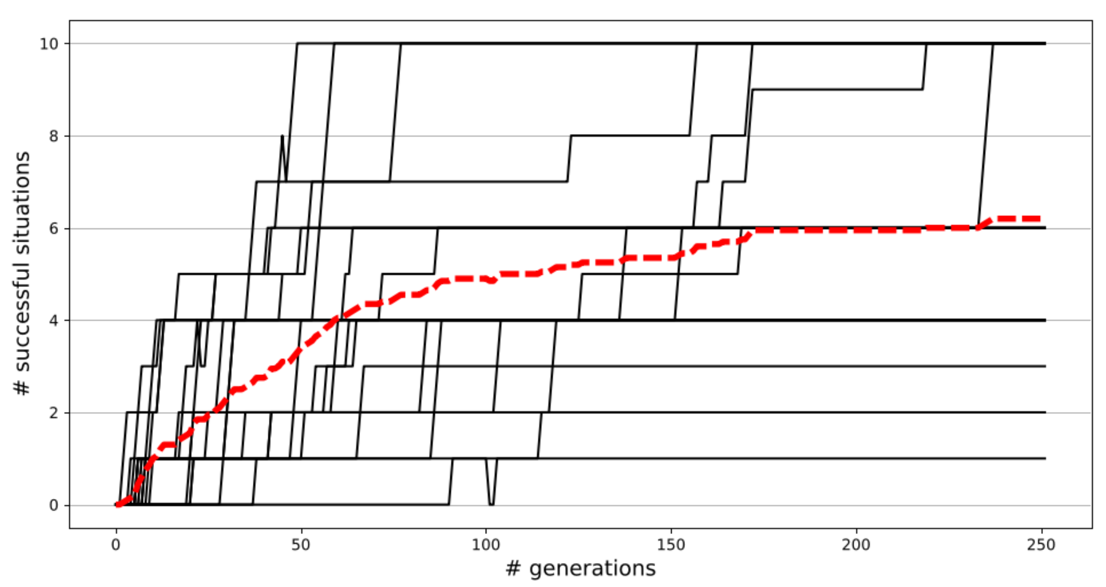

Figure 14 Dynamics of the number of successful situations for 20 independent runs of GP evolving the escaping behavior of a team of with 10 caribou agents

6. 4. Conclusion and Discussion

6. 4. 1. Conclusion

In conclusion, we would like to generalize the relationship between the number of caribou agents ("quantity") and the ability to escape. In all ten initial situations ("quality") the relationship is non-linear in that an increase of the number of agents does not necessarily yield an improved general (over all ten initial situations) ability to escape from the wolf. Rather, there is a distinct characteristic of the step function with a critical size (critical mass) – six – of the team of the caribou agents at which the escaping behavior becomes attainable.

Combined to the benchmark in which the group size is equal to eight, we found the best escaping strategy is obtained by the benchmark setting. Therefore, in the next experiments, the *default group size of caribou agents is set to eight*.

6. 4. 2. Discussion

Considering that, a single caribou could never escape from the superior wolf, the ability of a team of empathic caribou agents to escape may be viewed as an illustration of the emergent nature of a successful escaping behavior – in that the higher (team-) level properties are more than a mere sum of the properties of its individual entities. In this chapter, we presented empirical results that verify the complex (non-linear) nature of the relationship between the size of team of caribou agents and the efficiency of their escaping behavior.

The previous experiments show that the interactions and communications inside swarm can help the caribou agents to survive. Therefore, we were interested in verifying whether the efficiency of evolution or the behavioral effectiveness improved when we implement the swarming intelligence directly in the caribou agents.

In the next chapter, we will elaborate the detailed experimental setting and the experimental results.

Charpter-7

Verifying the Survival Value of Swarming

7.1. Introduction

Agent-based modelling and simulation (ABMS) is closely related to research into emergence and self-organization in natural and artificial systems consisting of social agents within the field of complex adaptive systems (CAS).

The ability of complex adaptive systems in nature to solve problems such as effective foraging for food, predator evading, or colony re-location through cooperation of multiple individual agents has inspired a number of approaches used in engineering that involve multiple computational agents. In these approaches, which are usually grouped under the term ‘swarm intelligence’, the aim is to harness the ability of complex adaptive systems to solve problems that are difficult to solve using alternative approaches, especially finding global optima in non-convex optimization problems[27].

In this chapter, we will explain how we constructed the comparison experiments, how we implement the swarming intelligence to the caribou agents and discuss the experimental results.

7. 2. Implementation of Swarm Intelligence

Swarming intelligence is a new feature for the benchmark WCP, namely, we cannot implement it by modifying or turn-on/off parameters. In order to implement swarming intelligence, we incorporated two additional features in WCP (shown in Table 4): (i) the distance to the geometrical centre of all the caribou agents that are seen by given caribou, (ii) the bearing of this centre, respectively. These two perceptions are implemented as two additional terminals in the set of terminal symbols of GP.

Table 4 Additional sets of terminals of GP used to implement swarming intelligence in caribou agents

Category		Designation	Explanation
Set of Terminals	Sensory abilities	PS_Emphasis_D	the distance to the geometrical centre of all the caribou agents that are seen by given caribou
		PS_Emphasis_A	the bearing to the geometrical centre of all the caribou agents that are seen by given caribou

Thus, during the evolution, caribou agents are able to consider – in the conditional parts of the evolved IF-THEN behavioral rules – the distance or bearing (or both) to the geometrical centre of the group of visible caribou agents. From another perspective, the centre of the swarm could be considered as an additional, yet invisible (virtual) caribou with well-perceivable distance and bearing.

7. 3. Experimental Setting

We use the experimental results obtained from eight empathic caribou agents as the benchmark (Figure 5), and conducted additional 20 runs of GP to evolve a successful escaping behavior of a team of eight empathic caribou agents with swarming intelligence as the comparison experiment.

Within the considered context of WCP, we view swarming behaviors as the ability of the caribou to understand in which direction it should move in order to become a part of (and seek a help from) the closest group of caribou agents. Thus, we implemented swarming behaviors by employing a well-perceived virtual caribou in the geometrical center of the group of visible caribou agents as mentioned in Subsection 7.2.

7. 4. Experimental Results

We obtained the experimental results and Figure 15 shows the dynamics of the number of successful situations for 20 independent runs of GP evolving a team of eight empathic caribou agents *with swarming* behaviors. On average (as depicted by the dashed line in Figure 15), the team of caribou agents escapes 8.4 (out of 10) initial situations.

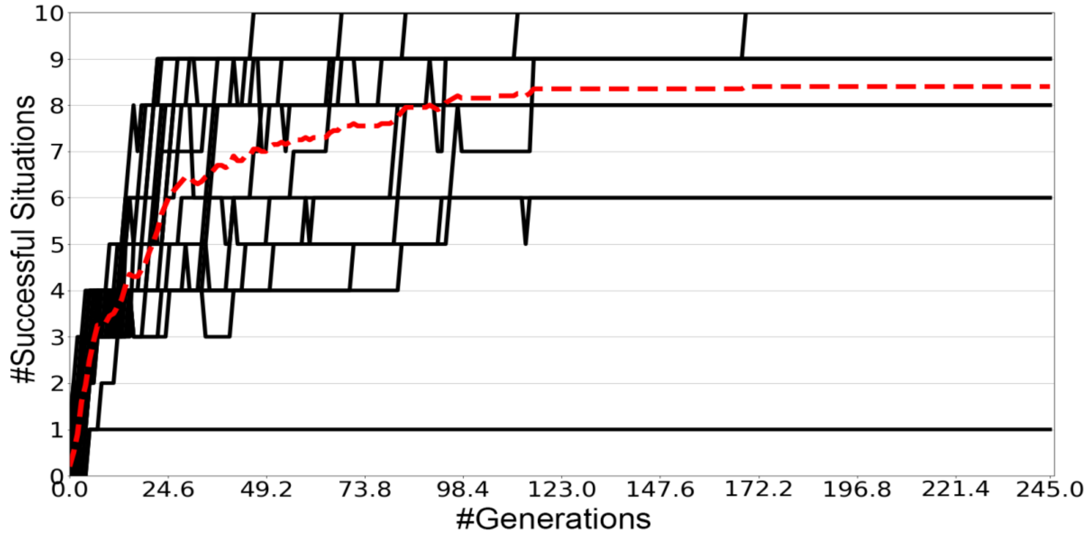

Figure 15 Dynamics of the number of successful situations for 20 runs of GP evolving a team of 8 empathic caribou agents with swarming behavior

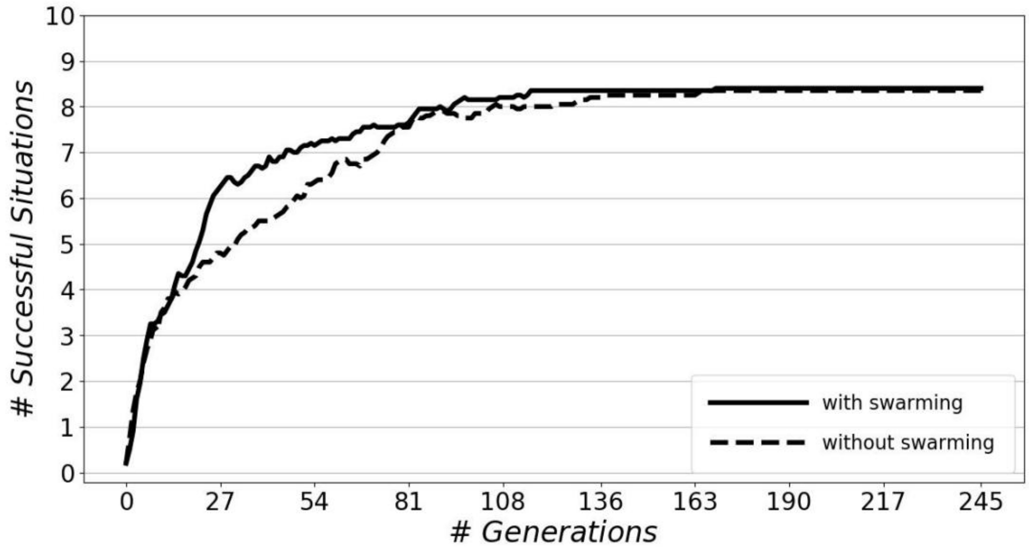

Figure 16 Dynamics of the average number of successful situations for 20 runs of GP evolving a team of 8 empathic caribou agents with and without swarming behavior

As Figure 16 illustrates, the dynamics of the improvement of average number of successful situations is virtually identical for both the caribou agents without- and with swarming up to generation #15. Between generations 16 and 40, however, the average number of successful situations of swarming agents is significantly higher than that of non-swarming agents. Finally, both of the dynamics converge to a similar final result of about 8.4 successful situations. The result of the team of swarming caribou agents, however, converges somehow faster than that of non-swarming ones. It suggests that the swarming contributes to the improvement of efficiency of evolution of the escaping behavior while preserving the effectiveness of such a behavior.

Figure 17 shows the results of statistical analysis using analysis of variance (ANOVA).

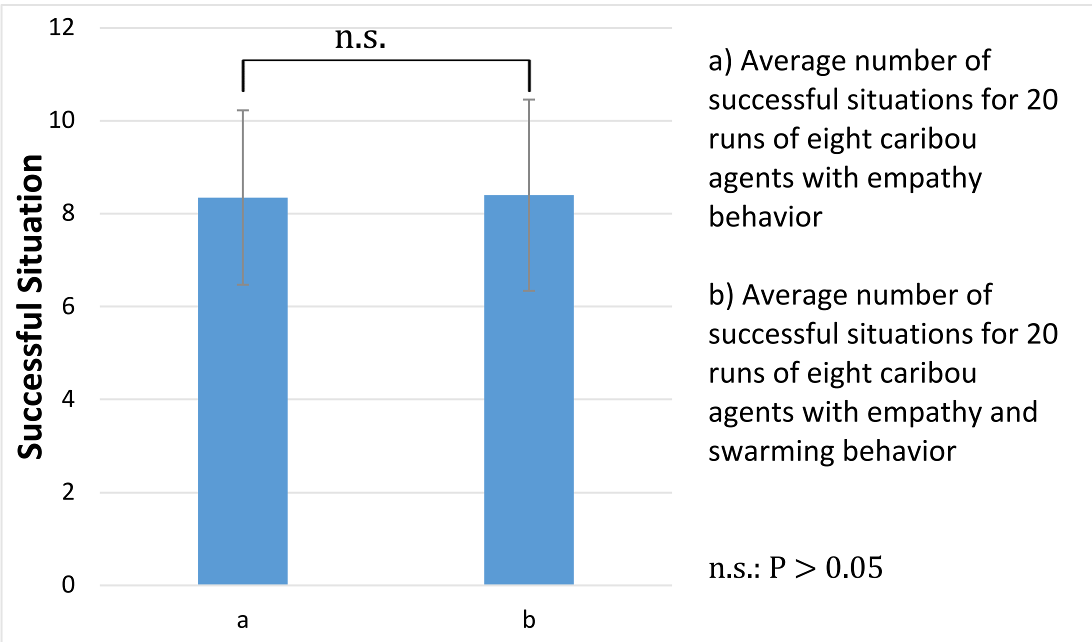

Figure 17 Experimental result of ANOVA test

Considering the concept of the ‘end of average’, and acknowledging that the figures only illustrate the average (over 20 independent runs) performance of the evolving teams of caribou agents, we also investigated the probability of success of the evolved two teams (with- and without swarming, respectively) of caribou agents. The probability of success is defined as the probability of achieving 90% of the desired result, i.e., successful escape in 9 out of 10 initial situations. In addition, we also calculated the computational effort of the simulated evolution of these two teams of caribou agents.

As the results shown in Table 5 indicate, the probability of success in evolving team of swarming caribou agents (65%) is higher than that of the team of caribou agents without swarming (60%). Considering this difference as not very significant, however, one could notice that both the average number of generations required to achieve all 10 initial situations and the analogical number to achieve 9 or 10 initial situations (be considered as successful trails) by the swarming agents (98.7 and 109.9, respectively) are about 10% lower than the average number of generations required for the team of caribou agents without swarming (109.9 and 137.4, respectively). Therefore, we could conclude that swarming contributes to the reduction of computational effort. The latter is defined as the average number of generations (or, analogically, average number of fitness trials) needed to achieve 90% of the desired result.

Table 5 Comparative analysis of the features of evolutionary runs of GP during evolution of two types of caribou agents – without- and with empathy, respectively

Feature of the Evolutionary Runs	Without swarming	With swarming
Number evolutionary runs resulting in all 10 successful initial situations	7	6
Number evolutionary runs resulting in 9 (of 10) successful initial situations	5	7
Probability of success	60%	65%
Average number of generations required for resolve all 10 initial situations	109.9	98.7
Average number of generations required to solve at least 9 (of 10) initial situations	137.4	127.9

7. 5. Conclusion and Discussion

7. 5. 1. Conclusion

We demonstrated a comparison experiment to investigate the survive value of swarming intelligence. From the experimental results, we found at the beginning of evolution, swarming intelligence can improve the efficiency of evolution, afterwards, the evolution converges to a similar value to the evolution without swarming. Even so , we still think that swarming intelligence has survive value, because in real life and in many case, we do not need a perfect solution and there are no perfect solution, we usually need a good enough and rapid responsible solution, namely, a solution can solve many problem at the beginning, just like the dynamics with swarming intelligence. On the other hand, the survive value of swarming intelligence is very limited in WCP, because empathy is also able to emerge swarming behaviors.

7. 5. 2. Discussion

Now, we know that, empathy is a very important factor to solve WCP problem, therefore, we were interested in verifying why the empathy can help the caribou agents escape from wolf. An empathic caribou agent will approach itself to help the exhausted chased peer riskily. It can be considered as an other-conscious behavior, hence, in the next chapter, we will investigate the dilemma between self-conscious and other-conscious.

7. 6. References

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Charpter-8

The Dilemma between Consciousness of the Self and Others

8.1. Introduction

We know that empathy can help caribou agents survive from wolf, in details, the empathic caribou will approach to the wolf riskily and help the exhausted and chased peer to survive. It can be considered as an other-conscious behavior.

As we know, we human beings are conscious, and many researchers are converging on the indicator: an animal is conscious, they propose, if it experiences the world subjectively. This captures the distinctive “me, here, now” element of our own experience [31].

Usually people agree with that consciousness comes with drawbacks. If it true, why not only human beings but also animals emerged consciousness during the evolution? And if there are no consciousness, i.e., if all animals are other-conscious, how it will influence the animals?

We conducted 4 comparative experiments to investigate the dilemma between self-conscious and other-conscious: i) 60 runs with both other-conscious and self-conscious, ii) 60 runs with other-conscious only, iii) 60 runs with self-conscious only and iv) 60 runs without both other-conscious and self-conscious.

8. 2. Implementation of Self-consciousness and Conscious of Others

We implemented self-conscious and other-conscious by modifying the perceptions of caribou agents. In this work, a self-conscious caribou agent means, the caribou agent that can see the speed of itself and knows that itself is chased by the wolf. On other hand, an other-conscious caribou agent means, the caribou agent that knows the distance and bearing of the chased peer and itself is faster than the chased peer (if the peer is existed).

Table 6 shows the perceptions we used in the comparison experiments, namely, it shows how we implement self-conscious and other-conscious.

Table 6 Different perceptions of comparison experiments

None	**Conscious (Self-conscious)**	**Empathy (Other-conscious)**	**Both**
Wolf_d	Wolf_d	Wolf_d	Wolf_d
Wolf_a	Wolf_a	Wolf_a	Wolf_a
	Speed	Chased_d	Speed
	Chased	Chased_a	Chased
		FasterOrEqual	Chased_d
			Chased_a
			FasterOrEqual

8. 3. Experimental Results

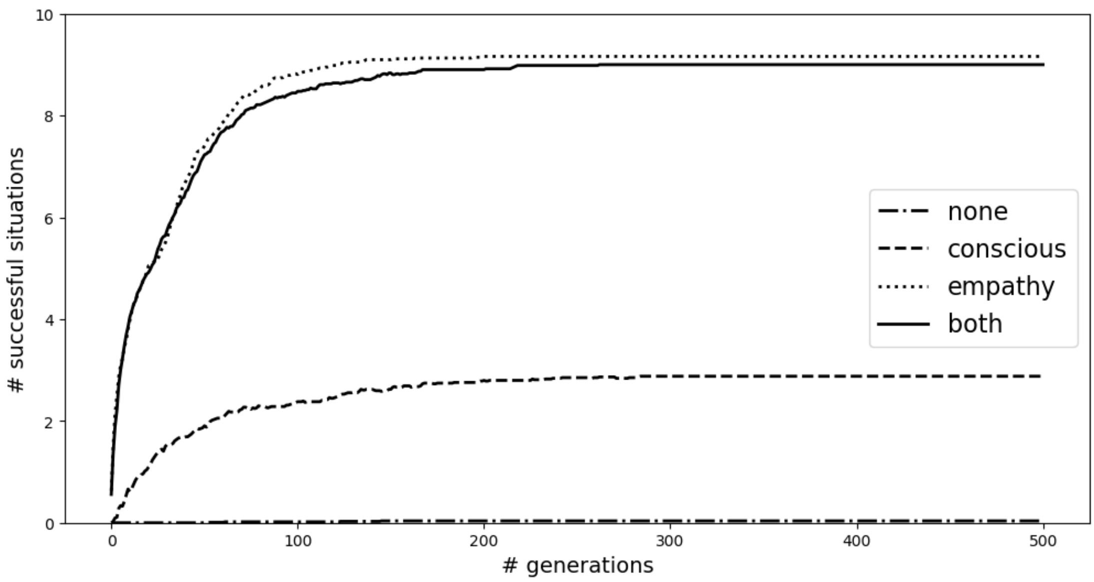

Figure 18 Dynamics of the average number of successful situations of the comparison experiments

Figure 18 shows the dynamics of the average number of successful situations of the comparison experiments.

We could find, without both self-conscious and other-conscious, the caribou agents are almost impossible to survive. The reason is simple, the caribou agents even cannot understand that they are under chased, and it cannot even be recognized as a life form.

The self-conscious-only caribou agents can escape in some situations. Because they at least know that they are in dangerous (be chased). But they cannot see the chased peer, hence, the self-conscious-only caribou agents cannot help the chased peer and distract the wolf, as a result, they can survive in and only in some limited situation.

Conversely to our expectations, the other-conscious-only caribou agents have the similar probability to survive as the caribou agents which have both self-conscious and other-conscious (we call, complete caribou agent), namely, self-conscious do not have survive value, because it cannot improve the escape strategy of other-conscious-only caribou agents.

This result is different from our experience, and then we rechecked the perception and found the reason, that other-conscious-only caribou agents have the perception “FasterOrEqual”. In fact, “FasterOrEqual” is a complex perception that mix self-conscious with other-conscious, namely, it considers both the speed of chased peer (other-conscious) and speed of itself (self-conscious). This changes the other-conscious-only caribou agent to a “partial complete caribou agent”, and obtain the very similar behaviors as the complete caribou agent.

We fixed the mistake, and conducted 4 additional comparative experiments.

8. 4. Implementation of Self-conscious and Conscious of Others

We mentioned that we misclassified the perception “FasterOrEqual”, and Table 7 shows the perceptions we used in the new comparative experiments.

Table 7 Different perceptions of comparative experiments (fixed)

None	Conscious (Self-conscious)	Empathy (Other-conscious)	Both
Wolf_d	Wolf_d	Wolf_d	Wolf_d
Wolf_a	Wolf_a	Wolf_a	Wolf_a
	Speed	Chased_d	Speed
	Chased	Chased_a	Chased
			Chased_d
			Chased_a
			FasterOrEqual

8. 5. Experimental Results (Fixed)

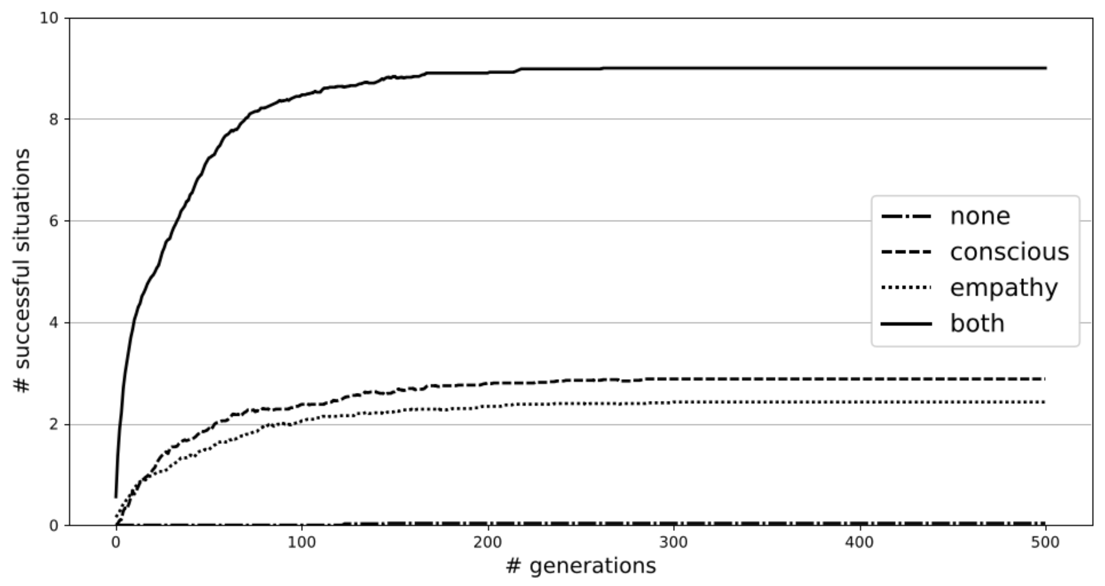

Figure 19 Dynamics of the average number of successful situations of the fixed comparison experiments

Table 8 Super-additive effect

Model	Average
Self-conscious only (a)	2.42
Other-conscious only (b)	2.90
Both (a + b)	8.98

* f (a + b) > f(a) + f(b)

Figure 19 illustrated the dynamics of the average number of successful situations of the fixed comparison experiments. From Figure 19, we could find that the behavioral effectiveness of other-conscious-only caribou agents become lower, and the curve is very similar to the curve of self-conscious-only caribou agents. The reason is that, if a caribou agent is other-conscious-only, it will approach to the wolf in order to help the chased peer, even the chased peer is stronger or itself is already exhausted. These behaviors are more like suicide rather than social behaviors.

We could conclude from this, that both self-conscious-only and other-conscious-only cannot help the caribou agents to survive. Therefore, in order to survive, caribou agents must be self-conscious and be other-conscious at the same time, namely, caribou agents have to solve the dilemma between self-conscious and other-conscious. Furthermore, we found the super-additive effect in the experiments shown in Table 8. The average number of successful situations of self-conscious-only and other-conscious-only is 2.42 and 2.90, respectively. The sum of those two values is 5.32 and smaller than the average number of successful situations of complete caribou agent (have both self-conscious and other-conscious) which is 8.98. This can be considered as the super-additive effect.

8. 6. Conclusion and Discussion

8. 6. 1. Conclusion

We demonstrated comparison experiments to investigate dilemma between self-conscious and other-conscious. From the experimental results, we found caribou agents without both self-conscious and other-conscious are almost impossible to survive. But when they have self-conscious or other-conscious, they have a chance to survive in a limited situation. When and only when the caribou agents have both self-conscious and other-conscious, then they can survive in most of the situations.

We also found the super-additive effect in the experiments. Super-additive effect can be described like:

$$f(x+y) \geq f(x) + f(y)$$

In this work, *f* is the simulation, *x* is self-conscious and *y* is other-conscious. And from the experimental results, we know that *f(x)* equal to 2.42, *f(y)* equal to 2.90 and *f(x+y)* equal to 8.98, which is satisfy the above formula[28].

8. 6. 2. Discussion

We found an interesting behavior from all the experiments above, that when some caribou agents approach to the wolf, usually they will run to the front of wolf, instant of run toward to the wolf simply. This behavior can be considered as a pro-activate behavior.

In next Chapter, we will investigate the dilemma between pro-activate and re-activate.

8. 7. References

- [28] Bob Holmes, "what's the point of consciousness?", New Scientist, 13 may, pp.28-31, 2017
- [31] New Scientist, Helen Thomason, Caroline Williams and Graham Lawton, "The Brain: A User's Guide", Nicholas Brealey Publishing, 2018

Charpter-9

The Dilemma Between Proactive and Reactive Behaviors

9. 1. Proactive Behavior of Caribou Agents

A reactive agent promptly responds ("reacts") to the changes in the perceived environment without considering any additional information (memory, current state, final goal, etc.). Conversely, the proactive agent engages in deliberate decision making according to its memory information, current state, and action plan about how to achieve its final goal, often regardless of its the current perception information. Compared to the reactive agents, introduction of pro-activeness in the behavior of agents might be beneficial for the success of the team of such agents, especially when the latter is situated in a competitive environment. However, proactive agents may also incur higher costs in the form of either a higher mortality rate because they take additional risks in dangerous environments or of engagements in unnecessary confrontations over shared resources[7].

In order to examine the effect of pro-activeness on the efficiency of evolution or the effectiveness of the evolved behavior of caribou agents, we implemented a pro-activeness architecture in the evolved Distracting (corresponding to the highest priority, social behavior) module of the caribou agents.

9. 2. Implementation of Proactive Behavior of Caribou agents

In the proposed implementation, the caribou agents feature a first in first out queue (FIFO-queue) of simple behaviors. The series of these behaviors is intended to mimic the “action plan” of the caribou agents. When empty, the queue is filled with multiple commands from the evolved IF-THEN rules, the conditional part of which satisfy the current environmental conditions. After being placed in the queue, the behaviors are extracted from the queue and executed by the agents in consecutive time steps pro-actively, regardless of the current perception information, as illustrated in Figure 200. Thus, the number of behaviors that are inserted into the queue would reflect the trade-off between the reactiveness (when few, or just one behavior is inserted into the queue) and pro-activeness (with several behaviors being inserted into the queue) of the overall behavior of caribou agents.

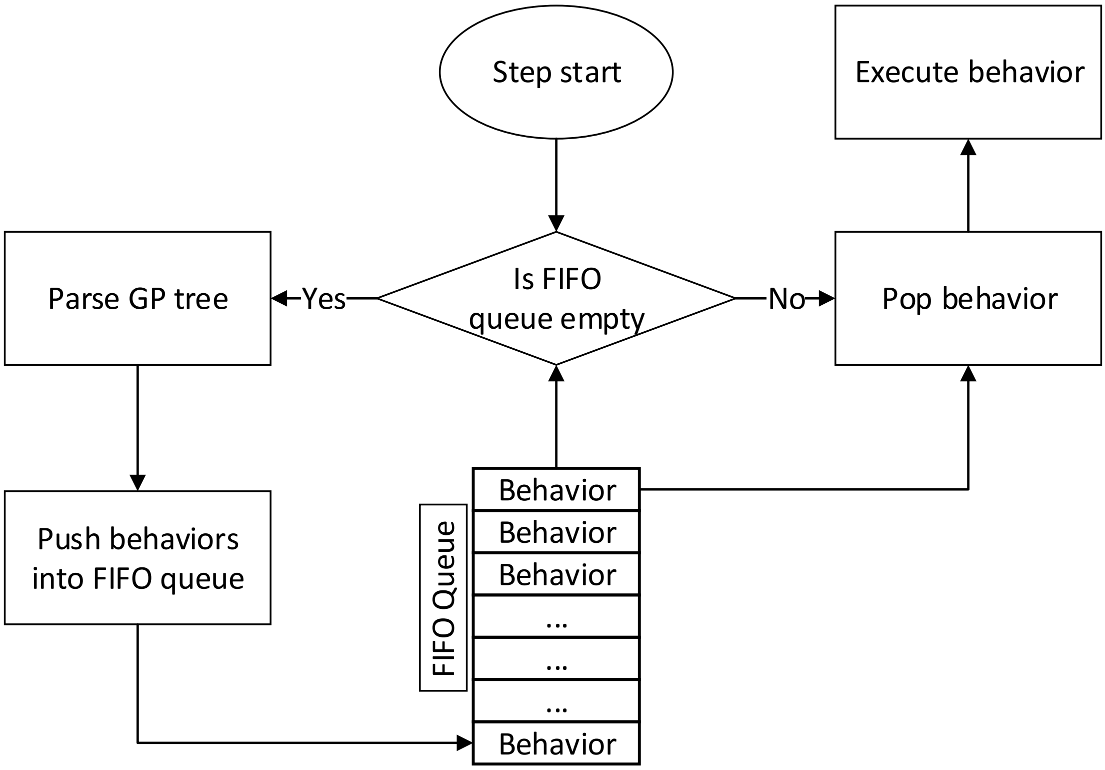

Figure 20 Time step-wise functionality of caribou agents

9. 3. Evolving proactive behavior of caribou agents in WCP

In the adopted GP framework, the evolved genetic program represents a set of IF-THEN rules. The conditional (IF) part contains a logical condition involving the currently perceived environmental information. The action (THEN) part of each of the rules contains one or a series of several simple behaviors (actions) to be executed by caribou agents. These behaviors, as shown in the row “Moving abilities” in Table 2 include, for example, behaviors like Turn_to_some_angle, Go_with_some_speed, Stop, etc. Each time when the FIFO-queue of actions is empty, the evolved set of IF-THEN rules are parsed and one (in case of preponderant reactiveness) or multiple (in case of preponderance of pro-activeness) simple behaviors pertinent to the action

(THEN) part of the IF-THEN rules which satisfy current environmental conditions, defined by the IF-part of these rules, are inserted into the queue.

Figure 21 shows the human-readable representation (in pseudo-code) of sample evolved IF-THEN behavioral rule of caribou agents.

```
if (speed < speed_wolf) then
begin
    turn(peer_a + 10);
    go_1.0;
end;
```

Figure 21 A human-readable representation of sample evolved IF-THEN behavioral rule

As depicted in Figure 21, the action part of the sample rule includes a series of just two simple behaviors – turning to a specified angle and running at 100% of the maximum speed of the agent. These two behaviors would be inserted into the queue (providing that the conditional part of the rule is satisfied, i.e., the speed of the agent is lower than that of the wolf) when the action FIFO-queue empties. The same two behaviors will be executed consecutively in the current- and the next time step, respectively. The environmental conditions during the latter time step might not necessarily still satisfy the IF-condition of the considered rule.

Therefore, by varying the maximal number of behaviors (denoted as maxNB) in the action part of evolved set of IF-THEN rules, we were able to control the trade-off between pure reactiveness (maxNB equal to one) and pro-activeness (maxNB equal to, say, 4) in the evolved behavior of the caribou agents.

9. 4. Experimental results

We conducted experiments with four different values of the maximal number of simple behaviors (maxNB) in the action part of evolved IF-THEN rules as follows: maxNB=1, maxNB=2, maxNB=3, and maxNB=4. The remaining parameters of the experimental setting were identical to those presented in previous sections of this article. The experimental results are summarized in Figure 22. Figure 23 shows the results of statistical analysis using analysis of variance (ANOVA).

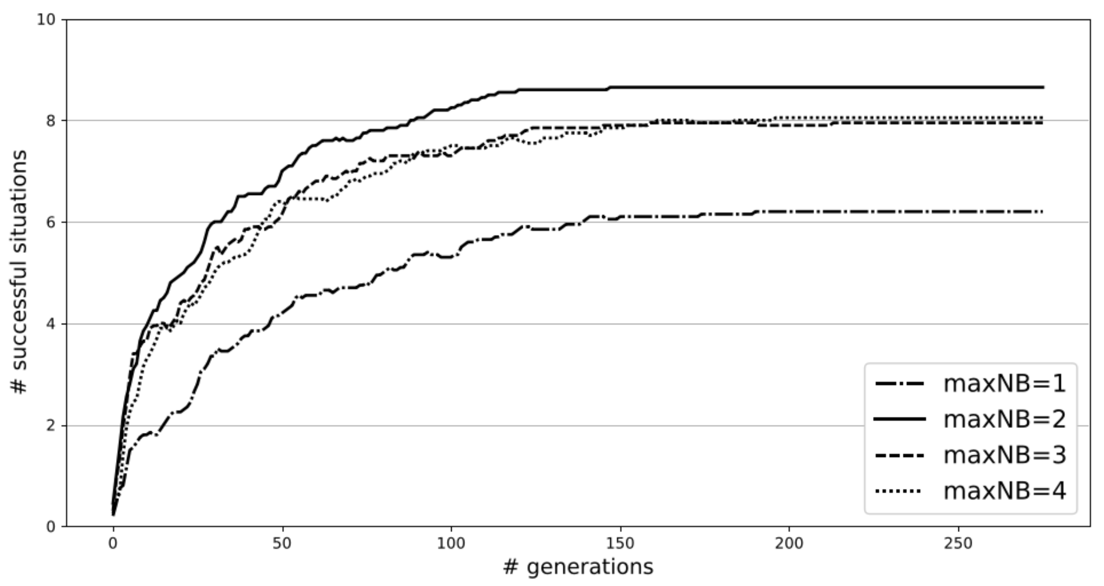

Figure 22 Dynamics of the average number of successful situations for 20 independent runs of GP for evolution of successful escaping behavior in a team of eight empathic caribou agents with different maximum number of consecutive simple behaviors (denoted as maxNB) in evolved IF-THEN rules

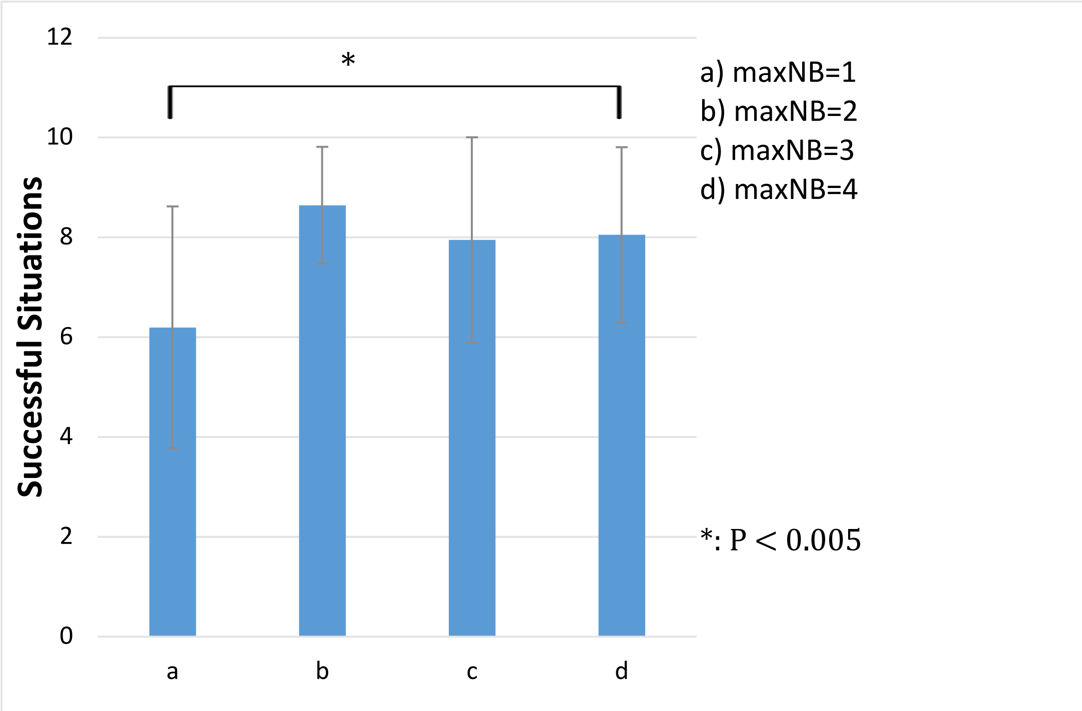

Figure 23 Experimental result of ANOVA test

9. 5. Discussion

As Figure 22 depicts, the efficiency of evolution – manifested by the dynamics of the average number of successful situations – of purely reactive agents (maxNB=1) is relatively poor. Both the maximum number of successful situation (6 out of 10) – indicating the effectiveness of the evolved escaping behavior – and the speed of achieving this number (around the 190th generation) are comparatively low. For maxNB equal to 3 and 4, both the efficiency of evolution and the number of successful situations improve compared to these of purely reactive agents. The best results are achieved, however, for the maxNB equal to 2, which suggests that a trade-off between reactive and proactive behavior in the caribou agents facilitates both efficiency of evolution and the effectiveness of their escape behavior.

We evaluated the effect of the maximum number of consecutive simple behaviors in the evolved IF-THEN rules of caribou agents on the probability of success and the computational effort of GP. The results are summarized in Table 9 below. Being an obviously inferior, the results obtained from the evolution of purely reactive caribou agents (maxNB=1) are omitted from Table 9.

Table 9 Comparative analysis of the features of evolutionary runs of GP during evolution of caribou agents with different number of maxNB

Feature of the Evolutionary Runs	**Value of maxNB**		
	2	**3**	**4**
Number evolutionary runs resulting in all 10 successful initial situations	3	4	3
Number evolutionary runs resulting in 9 (of 10) successful initial situations	12	8	10
Probability of success	75%	60%	65%
Average number of generations required for resolve all 10 initial situations	125.3	99.3	132
Average number of generations required to solve 9 (of 10) initial situations (including stagnation of fitness for 60 generations)	144.9	191.4	192.7

As the results shown in Table 9 suggest, the best values of both the probability of success and computational effort (i.e., number of generations required to achieve a resolution in 90% of initial situations) are achieved by the team of caribou agents that trade-off the reactivity and pro-activity (maxNB=2) of their behavior. Indeed, for the considered configuration of the evolved caribou agents, the probability of success is 75%, which is higher than the other configurations (60% and 65% for maxNB=3 and maxNB=4, respectively). The computational effort, corresponding to the number of generations (or, analogically, fitness evaluations) needed to resolve 9 (out of 10) initial situations, was 144.9 for maxNB=2, which is significantly lower than those of the alternative configurations (191.4 for maxNB=3, and 192.7 for maxNB=4).

Therefore, we can conclude that the purely reactive behavior (maxNB=1) of caribou agents could not contribute to an effective solution to the WCP. On the other hand, with an increase in the degree of pro-activeness (maxNB>2), the number of inactivated fragments of evolved IF-THEN behavioral rules increases, which resulted in both (i) an increase of the amount of neutral genetic code (introns) and (ii) an increase of the search space of evolution. Both factors are proven to have a detrimental effect on the efficiency of evolution. Finally, an optimal trade-off between the reactiveness and pro-activeness was achieved for maxNB=2, in that it results in the best possible efficiency of simulated evolution of the escape behavior of caribou agents.

9. 6. Conclusion

We summarize our finding that a limited pro-activeness introduced in the behavior of caribou agents contributes to the improvement of both the efficiency of evolution of their escape behavior and the effectiveness of such a behavior. Moreover, the trade-off between the pro-activeness and reactiveness in the escape behavior of caribou agents facilitates the achievement of the best results.

In our current research, we haven't done any frequency analysis of the appearance of combinations of particular commands in the FIFO buffer. We assume it could be very difficult to infer the importance of these particular commands, because, usually, in the complex systems, such as MAS, there could be a gap between the overall behaviour of the system as a whole, and the behaviour of its entities. However, this could be one of the promising directions of our future research.

Charpter-10

Fuzzy VS Non-Fuzzy Architecture of Caribou Agents

10. 1. Introduction

We found in our experiments all the sensors return a numerical value, and that it is i) not realistic, ii) not robust with noise. Therefore, we employed fuzzy logic to caribou agents and expected obtain a good-effectiveness and noise-robust system.

10. 2. What is Fuzzy Logic

The term "fuzzy logic" has been used since the late sixties. At first, it had the meaning of any logic possessing more than two truth values. Later on, after the famous paper of L. A. Zadeh it received two other meanings, namely the *theory of approximate reasoning* and the *theory of linguistic logic*. The latter, somewhat marginal theory, is one of logics whose truth values are expressions of natural language (for example, *true*, *more or less true*, etc.). The former is the main most often used meaning.

In general, fuzzy logic can be characterized as the *many-valued logic with special properties aiming at modelling of the vagueness phenomenon and some parts of the meaning of natural language via graded approach*. L. A. Zadeh formulates paradigm of fuzzy logic as follows: “In a narrow sense, fuzzy logic, FLn, is a logical system which aims at formalization of approximate reasoning. In this sense FLn is an extension of multi-valued logic. However, the agenda of FLn is quite different from that of traditional multi-valued logics. In particular, such key concepts as the concept of a linguistic variable, canonical form, fuzzy if-then rule, fuzzy quantification and defuzzification, predicate modification, truth qualification, the extension principle, the compositional rule of inference and interpolative reasoning, among others, are not addressed in traditional systems[29].”

10. 3. Outline of the Agenda of Fuzzy Logic

10. 3. 1. Linguistic Variable

One of the fundamental concepts introduced by L. A. Zadeh is that of linguistic variable. It is the quintuple:

$$<x, T(x), U, G, M>$$

where x is the *name of the variable*, T(x) is the set of its values (term set) which are linguistic expressions (syntagms), U is the universe, G syntactical rule using which we can form syntagms A, B... $\in \tau(X)$, and M is semantical rule, using which every syntagm $A \in T(X)$ is assigned its meaning being a fuzzy set A in the universe U, $A \subset U$.

A typical example of the linguistic variable is X:=Age. Its term set T(Age) consists of the syntagms such as *young*, *very young*, *medium age*, *quite old*, *more or less young*, *not old but not young*, etc. The universe U⊆R is some set of real numbers (note that we may speak about age of various things). The syntactic rule *G* may be a context-free grammar. The semantic rule *M* assigns meaning to the terms from T(Age) being various modifications of fuzzy sets depicted on Figure 24. Clearly, there is a lot of other linguistic variables, such as "height, size, temperature, press", etc.[29]

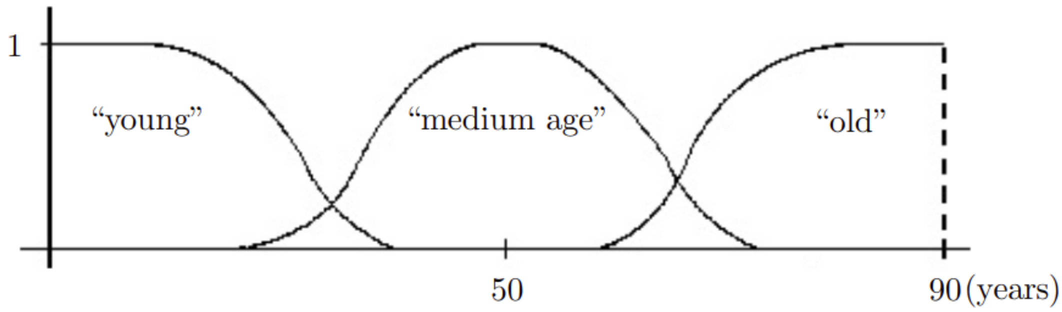

Figure 24 Possible forms of the fuzzy sets assigned as the meaning to the basic syntagms "small", "medium age", "old" from T(Age)

10. 3. 2. Approximate Reasoning

Linguistic variables have a quite wide scope of applications. The most important is their use in the approximate reasoning scheme, such as the behavior of the car driver below:

Condition:	IF the obstacle is *near* AND the car speed is *big* THEN break *very much*
	IF the obstacle is *far* AND the car speed is *rather small* THEN break *a little*
Observation:	the obstacle is *quite near* AND the car speed is *big*
Conclusion:	break *quite much*

This scheme contains vague expressions both in the condition consisting of the so called *fuzzy IF-THEN rules*, as well as in the observation. Note that such scheme is quite natural for the human mind. As a matter of fact, when driving a car, the outer conditions vary so much that we could hardly drive without ability to cope with vaguely stated rules. This is a very strong feature of our mind possible mainly due to its ability to cope with the vagueness phenomenon. Any attempt to give precise solution of tasks like this (think, e.g. about solution of the parking a car) necessarily fails. And it is a great challenge to find a formal system enabling to mimic human mind (at least in approximate reasoning schemes like that above).

Fuzzy logic offers a model of the above approximate reasoning scheme. The original proposal of L. A. Zadeh is the so-called *generalized modus ponens*[29].

10. 4. Experimental Setting

10. 4. 1. Implementation of Fuzzy Logic

We implemented the fuzzy logic by improving the IF-THEN rule to the fuzzy IF-THEN rules in six perceptions and behaviors which are elaborated in the next.

10. 4. 2. Implementation of Fuzzy Distance

We implemented fuzzy distance for the perception of *wolf*, *peer* and *chased peer*, and we defined three syntagms: *close*, *normal* and *faraway*. This fuzzy IF-THEN rule has two boolean operators: *is* and *not.* The structure of IF-THEN codes of evolved program are shown as follow:

```
Try:
   if <VAR_FDistance> <OPER_Fbool> <Fuzzy_Distance>:
      # do something
Catch e:    # if invisible
      # do something
```

The meaning of symbols used the fuzzy IF-THEN rules are shown is Table 10.

Table 10 Detail implementations of the fuzzy IF-THEN rules for *distance*

Fuzzy symbol	**Fuzzy symbol value**	**implementation**
VAR_FDistance	Peer	Closest caribou
	Enemy	Wolf
	Chased	Chased caribou
OPER_Fbool	Is	==
	Not	!=
Fuzzy_Distance	Close	Distance ∈ [0, 200)
	Normal	Distance ∈ [200, 400)
	Faraway	Distance ∈ [400, sensor range)

10. 4. 3. Implementation of Fuzzy Bearing

We implemented fuzzy bearing (visible angle) for the perception of *wolf*, *peer* and *chased peer*, and we defined four syntagms: *front*, *left, right* and *back*. This fuzzy IF-THEN rule has two boolean operators: *is* and *not*. The structure of IF-THEN codes of evolved program are shown as follow:

```
Try:
    if <VAR_FAngle> <OPER_Fbool> <Fuzzy_Angle>:
        # do something
Catch e:    # if invisible
        # do something
```

The meaning of symbols used the fuzzy IF-THEN rules are shown is Table 11.

Table 11 Detail implementations of the fuzzy IF-THEN rules for *angle*

Fuzzy symbol	**Fuzzy symbol value**	**implementation**
VAR_FAngle	Peer	Closest caribou
	Enemy	Wolf
	Chased	Chased caribou
OPER_Fbool	Is	==
	Not	!=
Fuzzy_Angle	Front	Angle ∈ [-30, 30]
	Left	Angle ∈ [-120, -30]
	Right	Angle ∈ [30, 120]
	Back	Angle ∈ {[-180, -120]U[120, 180]}

10. 4. 4. Implementation of Fuzzy Speed

We implemented fuzzy speed for the perception of *I,* and we defined four syntagms: *vigorous*, *normal, tried* and *exhausted*. This fuzzy IF-THEN rule has two boolean operators: *is* and *not.* The structure of IF-THEN codes of evolved program are shown as follow:

```
Try:
    if <VAR_FSpeed> <OPER_Fbool> <Fuzzy_Speed>:
        # do something
Catch e:    # if invisible
        # do something
```

The meaning of symbols used the fuzzy IF-THEN rules are shown is Table 12.

Table 12 Detail implementations of the fuzzy IF-THEN rules for *speed*

Fuzzy symbol	**Fuzzy symbol value**	**implementation**
VAR_FSpeed	I	Current caribou
OPER_Fbool	Is	==
	Not	!=
Fuzzy_Speed	Vigorous	Energy $\in \{x \mid x>0.9\times \text{max\_energy}\}$
	Normal	Energy $\in \{x \mid x\leq 0.9\times \text{max\_energy} \text{ and } x>0.75\times \text{max\_energy}\}$
	Tried	Energy $\in \{x \mid x\leq 0.75\times \text{max\_energy} \text{ and } x>0.6\times \text{max\_energy}\}$
	Exhausted	Energy $\in \{x \mid x<0.6\times \text{max\_energy}\}$

10.4.5. Implementation of Fuzzy <Chased>

We implemented fuzzy chased for the perception of *I,* and we defined one syntagms: *chased*. This fuzzy IF-THEN rule has two boolean operators: *is* and *not.* The structure of IF-THEN codes of evolved program are shown as follow:

```
if <VAR_FExtend> <OPER_Fbool> <Fuzzy_Extend>:
    # do something
```

The meaning of symbols used the fuzzy IF-THEN rules are shown is Table 13.

Table 13 Detail implementations of the fuzzy IF-THEN rules for *chased*

Fuzzy symbol	Fuzzy symbol value	implementation
VAR_FExtend	I	Current caribou
OPER_Fbool	Is	==
	Not	!=
Fuzzy_Extend	Chased	Current caribou is the target of wolf

10.4.6. Implementation of Fuzzy <Stronger Than>

We implemented fuzzy stronger for the perception of *I,* and we defined four syntagms: *stronger*. This fuzzy IF-THEN rule has two boolean operators: *is* and *not.* The structure of IF-THEN codes of evolved program are shown as follow:

```
Try:
    if <VAR_FExtend> <OPER_Fbool> <Fuzzy_Extend_NA>:
        # do something
Catch e:    # if invisible
        # do something
```

The meaning of symbols used the fuzzy IF-THEN rules are shown is Table 14.

Table 14 Detail implementations of the fuzzy IF-THEN rules for stronger

Fuzzy symbol	**Fuzzy symbol value**	**implementation**
VAR_FExtend	I	Current caribou
OPER_Fbool	Is	==
	Not	!=
Fuzzy_Extend_NA	Stronger	Energy≥energy_of_chased_caribou

10. 4. 7. Implementation of Fuzzy Turning Behaviors

After we implemented fuzzy logic in caribou agents, namely, instant of the numeric angle from current heading which used in our previous experiments, now the caribou agent can only know several syntagms such as front, left, right and back. This changes not only affect the perception but also influence the behavior, because if the caribou agent does not know the numeric angle, how it turns 16 degree, for example. Therefore, we implemented a fuzzy turn behavior to solve this problem. On the other hand, <Go> behaviors can be considered as fuzzy behaviors already: run in different percentage of max speed can be viewed as run in different syntagm of speed.

We implemented two type of fuzzy behaviors, i) *turn_to_<object>* and ii) *turn_away_from_<object>*. In them, *<object>* may be any agent, such as *wolf, closest peer, chased peer*. When a caribou agent is executing fuzzy turn behavior, it will a turn a fixed angle depended on the current relative position. For example, one caribou agent is executing *turn_to_wolf*, and the wolf is on the right side on the current caribou agent, then the caribou agent will turn right 10 degree. Table 15 shows the implementation of fuzzy turn behaviors.

Table 15 Implementation of fuzzy turn behaviors

	Turn_to_<object>	**Turn_away_from_<object>**
<Object> is front	-	Turn_right_90°
<Object> is left	Turn_left_10°	Turn_right_20°
<Object> is right	Turn_right_10°	Turn_left_20°
<Object> is back	Turn_left_90°	-

10. 5. Experimental Results of Comparison of Fuzzy Logic with the Benchmark

We conducted comparative experiments with two caribou models: i) empathic caribou agents which were employed in the previous experiments as the benchmark, ii) empathic caribou agents with fuzzy logic incorporated in. We plotted the dynamics of the average number of successful situations of both models, and illustrated in Figure 25.

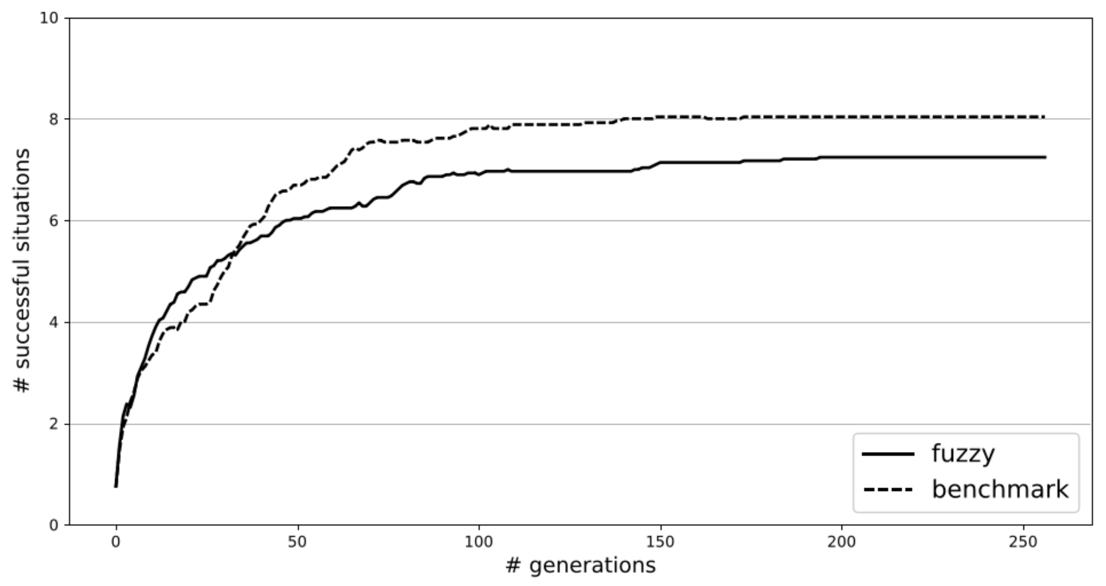

Figure 25 Dynamics of the average number of successful situations

As we predicted, the benchmark model has a higher average number of successful situations, i.e., *in average,* the benchmark model has higher behavioral effectiveness. The reason is that fuzzy logic reduced the huge numeral realm to a small syntagms realm. This change will deteriorate the behavioral effectiveness.

Moreover, our objective is investigating not only the behavioral effectiveness but also the efficiency of evolution of escape behavior. Hence, we plotted the probability of success of the comparison experiments, shown in Figure 26.

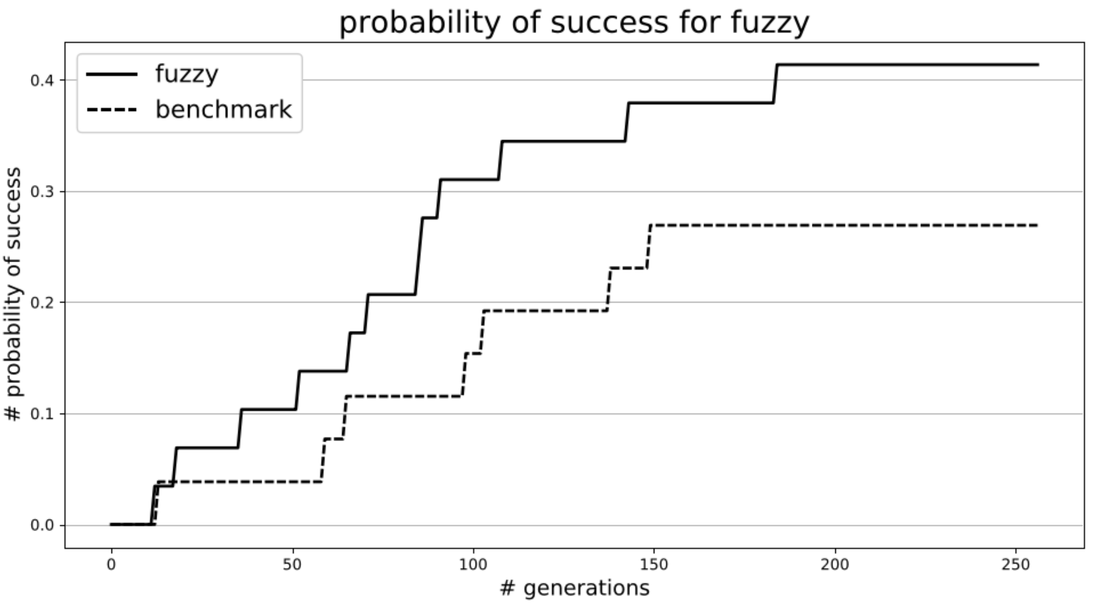

Figure 26 Dynamic of probability of success

In this experiment, success means caribou agents evolved a escaping strategy which can help all of them survive in all 10 situations. From the results, we can find that, the probability of success of empathic fuzzy caribou agents is significantly higher than the benchmark, i.e., better efficiency of evolution of escape behavior.

To sum up, empathic fuzzy caribou agents can find one success escaping much faster than the benchmark, with a small deterioration in the behavioral effectiveness. This result has realistic value, because in real life, there are no perfect solution, usually we just need to obtain a good enough and quick response solution.

Additionally, considering that, our fuzzy model is very simple and unadjusted, even so, fuzzy logic improves the efficiency of evolution of escape behavior significantly, consequently, we think the deterioration of behavioral effectiveness is acceptable.

10. 6. Experimental Results of Robustness to Noise

Noise is a pervasive workplace hazard that varies spatially and temporally, but we expected by employing fuzzy, we can obtain a noise-robust solution of WCP. Therefore, we implemented the noise to angle sensors of caribou agents (we experimentally proofed that the noise of distance sensors does not influence the evolution much) simply by adding a random number[30].

In order to verify the noise robustness, we chose 3 GP of all 10 situations solved GP from the results of benchmark. We tested them in i) 1000 random situations without noise, ii) 1000 random situations with a small noise within 5 degrees, and iii) 1000 random situations with a small noise within 10 degrees. We documented the successful situations, respectively, marked as r1, r2 and r3. Afterwards, we calculated d1=r2-r1, d2=r3-r1, in here, d1 and d2 to show how the noise influence the caribou agents. Finally, we illustrated the results in Figure 27.

Additionally, in order to compare the robustness, we chose 3 GP of all 10 situations solved GP from the results of fuzzy logic incorporated caribou agents, obtained d1, d2 by the same way, and illustrated the results in Figure 28.

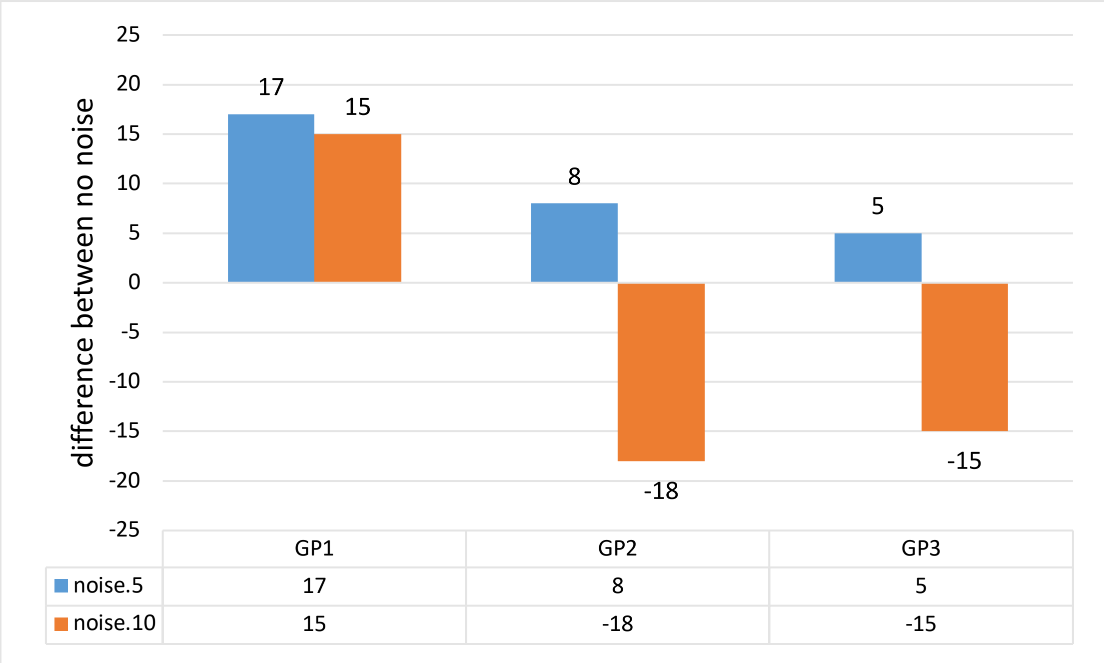

Figure 27 Influence of noise on benchmark caribou agents

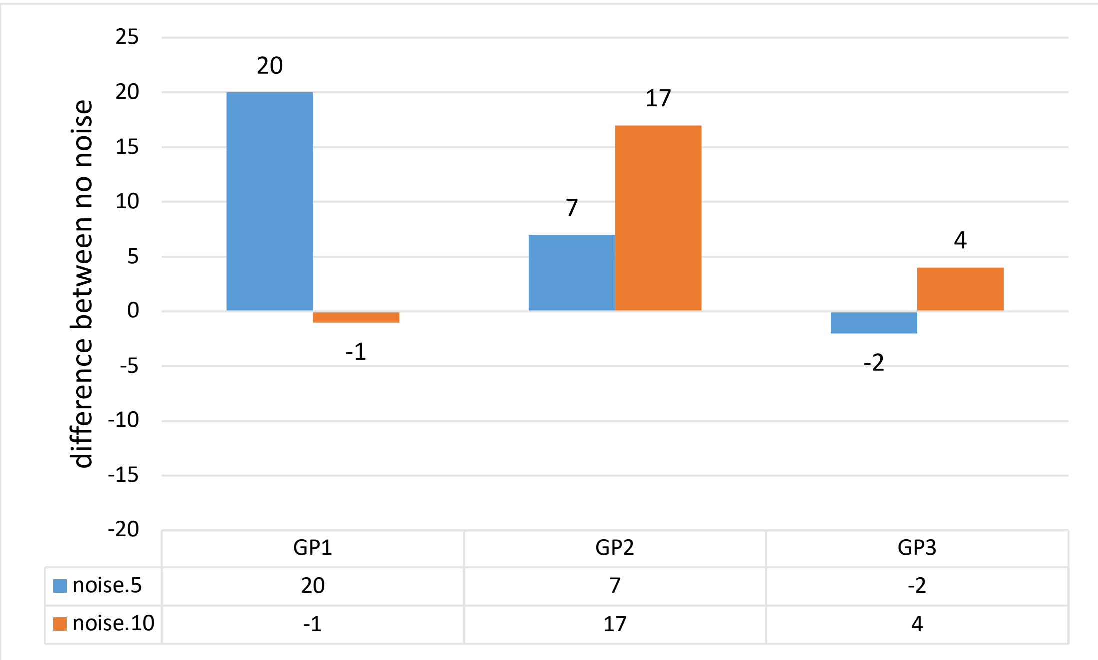

Figure 28 Influence of noise on fuzzy logic caribou agents

In Figure 27 and Figure 28, the number shows how the number of successful situations changes after adding noise in the environment. For example, in figure 28, the data of GP1 shows that, after adding a small noise within 5 degrees, the number of successful situations increased 20 compare to benchmark. But after adding a noise within 10 degrees, the number of successful situations reduced 1 compare to benchmark.

From Figure 27, we can find that for the benchmark caribou agents, the noise added in the environment can deteriorate the generality of the GP easily and significantly (two big negative changes). On the other hand, Figure 28 illustrated that for the caribou agents with fuzzy logic incorporated in, the influence of noise is very limited (two but very small negative changes).

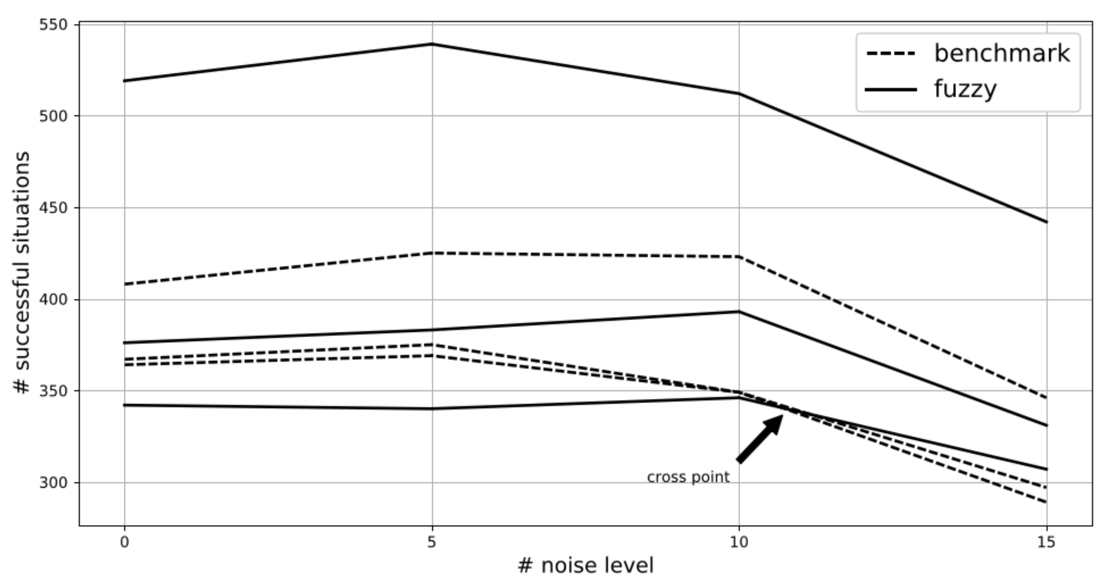

Figure 29 Dynamic of influence of noise level to the number of successful situations

From Figure 29 we can know that, i) in average, fuzzy can obtain a higher number of successful situations, ii) with the increase of noise level, the number of successful situations of fuzzy reduce slower, and iii) the worst GP in noise level 0 which is evolved by fuzzy, when noise level increase to 15, the worst GP of fuzzy surmount other two GP which is evolved by benchmark. Namely, the fuzzy logic can improve the robustness of system.

To sum up, we concluded that, fuzzy logic can i) allow caribou agents use cheaper angle sensors, ii) help caribou agents obtain an more noise robust, namely, more generality escaping strategy, and only with a very limited lost in behavioral effectiveness. This result has realistic meaning in robotics, because in real world usually people need to consider the cost of sensors, moreover, noise always exists in real world, e.g., in environment or sensors. Therefore, fuzzy logic is useful for investigating realistic problems.

But from the experimental results we found that, in many cases, adding a noise will increase the number of successful situations of 1000 test random situations. It seems the dithering effect and we are planning to investigate dithering effect in MAS in the future.

Dithering is an intentionally applied form of noise used to randomize, and eventually – to cancel – the error of quantization. Dithering is routinely used in processing of both digital audio and video data, and it is also used in mechanical engineering. Another common use of dithering is converting a greyscale image to black and white, such that the density of black dots in the new image approximates the average grey level in the original. In the domain of electronic signal, dithering could also be used to smooth a rugged signal.

Use a simple way to sum up, dither effect means “not all noise is bad”, sometime and in some cases, some noise can improve the quality of the system. The use of dithering is reported found in many fields, such as image-, video-, and audio-processing, in electronic and engineering. However, to the best of our knowledge, there is published report on the effect of dithering in MAS. The implementation of the fuzzy logic in our MAS rendered the latter a highly discrete one. Therefore, we speculate that the dithering somehow smoothed (made it more “analog”) such a highly discrete MAS.

10. 7. Conclusion

In this chapter, we introduced fuzzy logic in the caribou agents in order to obtain a more generality and robust escaping strategy. We implemented fuzzy logic in the perceptions of caribou agents (e.g., distance perception, angle perception, speed perception and energy perception) and the behaviors. Afterwards, we demonstrated a comparison experiment and verified that implement fuzzy logic can help caribou agents find the escaping strategy faster and only cost a limited behavioral effectiveness. Namely, fuzzy logic can improve the efficiency of evolution with a limited deterioration of behavioral effectiveness.

Moreover, we expected that fuzzy logic can help the caribou agents obtain a generality and more robust escaping strategy. In order to achieve this, we demonstrated a comparison experiment to compare how the small noise influence the number of successful situation of 1000 random test situations. From the experimental results, we found that the influence of noise is very limited to the caribou with fuzzy logic incorporated in. Therefore, we concluded that fuzzy logic contributes to obtain a generality and more robust escaping strategy.

Additionally, from the previous experiment, we found that in many cases, after adding a small noise, the number of successful situations was increased, in other words, by adding a small noise, generality and robustness was improved. It can be viewed as the dithering effect.

10.8. References

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Summary, Conclusion, and Future Work

11. 1. **Summary**

This study was initiated with the objective to investigate the feasibility of applying genetic programming (GP) to automatically evolve the escape behavior of a team of caribou agents. Moreover, we also examined whether some socio-psychological aspects introduced in caribou agents improved the efficiency of their simulated behavioral evolution or behavioral effectiveness.

In order to achieve our objective, we employed wolf-caribou pursuit problem (WCP) which can be viewed as a reversed instance of the well-studied predator-prey pursuit problem and originally defined and investigated by Tian, Tanev, and Shimohara.

Firstly, we constructed a comparative experiment to verify the survive value of empathy. From the experimental results, we can conclude that empathy improves both the efficiency of evolution of escape behavior and the effectiveness of such a behavior.

After that, we constructed another comparative experiment, and verified the survive value of the size of caribou group. Moreover, we obtained the current best model of caribou swarm in which the group size is eight and the caribou agents employed empathy, it was used as the benchmark in the next researches.

We verified the survive value of group size, so that, our next objective was to investigate whether the swarming intelligence can help caribou agents escape. Hence, we implemented swarming intelligence in caribou agents, but the experimental result did not show obvious correlation. That is because swarming behaviors can be emerged by empathy.

Afterwards, we were interested in verifying why the empathy can help the caribou agents escape from wolf. We found the most important perception (use in all evolved GP) can be viewed as a mix with self-conscious and other-conscious. Therefore, we constructed an experiment to investigate the dilemma between self-conscious and other-conscious. The experimental result shows that self-conscious only or other-conscious only cannot help the caribou agents to survive. But when self-conscious and other-conscious work together, both the efficiency of evolution and the behavioral effectiveness are improved. Furthermore, we found super additive in this experiment.

In all the experiments we discussed above, we found that when a caribou tries to help the chased peer by approaching itself, the caribou usually run to the front of wolf, instead of approaching towards the wolf simply. It can be considered as a pro-activate behavior. Therefore, we constructed an experiment to investigate the dilemma between pro-activeness and reactiveness and the result shows only a suitable pro-activeness (neither pure reactiveness nor deep pro-activeness) can improve the efficiency of evolution and the behavioral effectiveness.

Finally, we found in our experiments all the sensors return a numerical value, and that it is i) not realistic, ii) not robust with noise. Therefore, we employed fuzzy logic to caribou agents and expected obtain a good-effectiveness and noise-robust system. We implemented a very simple fuzzy model and the result shows the efficiency of evolution improved significantly with only a limited deterioration of behavioral effectiveness. Additionally, we found the dithering effect in WCP.

11. 2. Future Work

About the future work, we think there are three themes can be researched.

I) To investigate the effect of dithering on the efficiency of the escaping behavior of caribou agents in the proposed WCP.

II) The behavior of wolf agent is very easy and handcrafted. In the future, we can employ co-evolution and the concept of generative adversarial network (GAN). Namely, we can evolve the behavior of both wolf agent and caribou agents, after confrontation, the wolf agent and caribou agents evolve respectively.

III) The current fuzzy is very simple and unadjusted, therefore we can use co-evolution to evolve the definitions of the syntagms and find a better fuzzy model.

This work is only the beginning of investigating the wolf-caribou problem. For this reason, we employed a handcrafted wolf agent that only chases the closest peer. In the current version of the proposed system, we implemented a lot of socio-psychological aspects to help the caribou agents to escape.

As a second step, in the future we are planning to evolve both the (multiple) wolf- and (multiple) caribou agents, using the concept of competitive co-evolution in GP. We anticipate that that by evolving both types of (competing) agents, we can obtain some novel emerged behaviors and obtain an ecologically balanced system. Ultimately, we could verify the emergence of oscillating patterns of the number of both the wolfs and the caribous, consistent with the Lotka–Volterra equations.

Moreover, we also can combine both the two routes and develop a fuzzy WCP with complex modelled agents.

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