Effects of Empathy, Swarming, and the Dilemma between Reactiveness and Proactiveness Incorporated in Caribou Agents on Evolution of their Escaping Behavior in the Wolf-Caribou Problem

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Abstract: We investigate whether socio-psychological aspects such as empathy, grouping (swarming), and the trade-off between reactive and proactive behaviors, implemented in caribou agents improves the efficiency of the simulated evolution (via genetic programming) of their escape behavior or the effectiveness of such a behavior in the wolf-caribou predator prey pursuit problem. The latter comprises a team of inferior caribou agents attempting to escape from a single yet superior (in terms of sensory abilities, raw speed, and maximum energy) wolf agent in a simulated two-dimensional infinite toroidal world. We empirically verified the survival value of empathy in that it improves both the efficiency of evolution of escape behavior and the effectiveness of such a behavior. Also, we concluded that swarming facilitates a faster evolution of caribou agents while preserving the effectiveness of their evolved behavior. Finally, we investigated the dilemma between the reactivity and proactiveness of the behavior of caribou agents. The experimental results suggest that the trade-off between the reactivity and proactiveness facilitates a significant improvement of both the efficiency of evolution and the effectiveness of the evolved escape behavior of caribou agents.

Key Words: collective behavior, empathic agents, proactive-reactive behaviors, genetic programming.

1. Introduction

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 reactivity and proactiveness – improve the efficiency of the simulated evolution of their behavior or the effectiveness of such a behavior.

1.1 Wolf-Caribou Predator Prey Problem (WCP)

As an instance of such an artificial society mentioned above, we consider the wolf-caribou predator prey pursuit problem (WCP). The WCP, which was originally defined and investigated by Tian, Tanev, and Shimohara [2],[3], is an instance of a heterogeneous MAS featuring two types of agents – one superior wolf agent (predator) and multiple inferior caribou agents (prey) that must escape from the chasing wolf. Figure 1 illustrates a sample snapshot of the proposed WCP, comprising eight 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 like 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. 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. Thus, the WCP can be viewed as a reversed instance of the well-studied predator-prey pursuit problem. In the latter, a team of several inferior predators is required to capture a single superior prey.

1.2 Objective

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) and the trade-off (dilemma) between reactivity and proactiveness – 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 [4].

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 reactivity and proactiveness of caribou agents on the efficiency of evolution of their escape behavior.

1.3 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 handcraft 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 nonlinear, very complex, and too difficult to be formalized. Hence, we rely on GP, which is both a heuristic and holistic approach, to develop such behaviors.

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 behaviors 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.

1.4 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 [2],[3], 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 [4].

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 elaborate on the evolutionary framework and its main parameters. Section 4 presents the experimental results that verify the favorable effect of swarming on the efficiency of evolution of escape behavior while simultaneously preserving the effectiveness of such a behavior. Section 5 discusses the experimental results about the optimal trade-off between reactivity and proactiveness of the behavior of caribou agents. Finally, Section 6 draws a conclusion to our research.

2. Implementation of the WCP

2.1 Definition of the WCP

The employed instance of the WCP was comprised of two types of agents: a single predator wolf agent and multiple caribou agents, as illustrated in Fig. 1.

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 [5]–[7]. We model the world as a two-dimensional continuous (infinite) torus visualized as a 2D-surface with simulated (scaled down) dimensions 1800 m × 1800 m.

The moving abilities of caribou agents are also continuous; they can turn left and right to any angle from their current heading. Caribou agents can run at speeds equal to 0, 0.25, 0.5, 0.75 and 1.0 of their maximum speed. On the other hand, the wolf runs at its maximum speed when chasing the closest caribou. The behavior of the wolf agent is handcrafted, as the latter always chases the closest caribou agent. We consider such a simple, yet reasonably realistic behavior of the wolf as a first step towards the future development of a WCP in which the behaviors of both the wolf and caribou would be allowed to coevolve. Furthermore, all agents feature a gradual decrease in their energy level. The energy decreases linearly with the increase of the overall distance traveled by the agents since the beginning of the trial [4].

The perceptions of caribou agents are based on the proximity perception model: they can only see (i) the closest peer agent, (ii) the chased caribou agent (modeling the empathy of caribou agents), and (iii) the wolf, and only if these are within the limited range of visibility of their simulated sensors. The wolf agent can see (and chase) only the closest caribou and only if the latter is within the range of its sensors. The visual field of the sensors of both the caribou and wolf is 360 degrees [4].

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 en-
An eventual unhindered chase of a single caribou would inevitably result in a capture of the latter. Conversely, an eventual cooperative behavior of caribou agent would result in a longer and, therefore, sub-optimal zig-zag 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. Table 1 illustrates the main parameters of the wolf and caribou agents [4].

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  | 360°   | 360°    |
| Max speed                | 19 m/s | 17 m/s  |
| Initial energy           | 150 units | 100 units |

2.2 Architecture of the Caribou Agents

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

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

In our approach, the functionality of the module implementing social behavior is represented as a set of behavioral IF-THEN rules. Depending on the currently perceived sensory information, if the conditional (IF) part of the IF-THEN rules is satisfied, the caribou executes the evolved social behavior (implemented as THEN part in the behavioral rules). Otherwise, depending on whether the wolf is visible or not, the caribou agent will initiate either an escape or random wandering behavior, respectively.

Both the escape and random wandering are straightforward behaviors, and we handcrafted them in the functionalities of caribou agents. However, distracting (social behavior) of each caribou agent is the type of behavior that explicitly accounts for the behavior of other entities in WCP, and consequently, contributes to the emergence of the higher (team-) level escape behavior. Due to the enormous complexity of the relationship between the entity-level and the team-level properties of the WCP, we propose an approach for automated evolutionary development via GP of the social behavior (as a set of evolving IF-THEN rules) of the caribou agents. Details of the evolutionary framework are presented below.

3. Evolutionary Framework

We modeled 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) [8], and artificial neural networks. GP is a domain-independent problem-solving approach in which a population of individuals (encoded as computer programs) evolves – by means of modeling the Darwinian principle of reproduction and survival of the fittest – to solve various design-, control- and optimization problems [9]. In GP, 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

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, =, ≠, ≠, ≠, ≠ |
| Sensory abilities | Wolf_d        | Distance to the wolf                                                        |
|                   | Wolf_a        | Bearing (angle in the visual field) of the wolf                             |
|                   | Speed_Wolf    | Speed of wolf                                                               |
|                   | Peer_d        | Distance to the closest caribou                                            |
|                   | Peer_a        | Bearing (angle in the visual field) of the closest caribou                  |
|                   | Speed         | Own speed                                                                   |
|                   | Speed_Peer    | Speed of the closest caribou                                               |
|                   | Chased_Peer_d | Distance to the closest caribou                                            |
|                   | Chased_Peer_a | Bearing (angle in the visual field) of the closest caribou                  |
|                   | Chased        | True if caribou is the one being chased, False otherwise                   |
|                   | FasterThanChased* | True if own speed is higher than that of the caribou being chased, False otherwise |
| State variable    | Speed         | Speed of the agents(m/s)                                                   |
| Ephemeral constant| Integer       | Random value within [0…10]                                                 |
| Moving abilities  | Turn(a)       | Turns from the current orientation to 0 degrees (0–6 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 |

*Only for empathic caribou agents
functions and terminals of the proposed GP used to evolve the escape behavior of caribou agents [4]. The main attributes of GP – genetic representation, genetic operations, breeding strategy, and fitness function are elaborated in the following subsections.

3.1 Representation of Evolved Genetic Programs
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 [10].

3.2 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. labeled with the same XML-tag) from the selected parents can be swapped [11],[12]. 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 [4].

3.3 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.

3.4 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 60 m from the center 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 [4].

The fitness value calculated for each of these initial situations consists of the following three 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 [4].

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) |

3.5 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 [11] 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. Verifying the Survival Value of Empathy

4.1 Evolution of Team of Caribou Agents without Empathy

First, we conducted 20 independent runs of GP in an attempt to evolve a successful escaping behavior in a team of eight caribou agents without empathy. Within the considered context of the WCP, we view empathy as the ability of the caribou not currently chased by the wolf to understand and share the feelings of the one being chased.

4.2 Effect of Empathy on the Efficiency of Evolution and Effectiveness of Evolved Escape Behavior

We conducted additional 20 runs of XGP to evolve a successful escape behavior of a team of eight empathic caribou agents. We incorporated empathy by introducing additional perceptions that allow the caribou agents to perceive the distance and bearing of the currently chased caribou (Table 2). It should be noted that the introduction of empathic perceptions does not automatically imply an emergence of compassionate behavior (i.e., a stronger caribou attracts the attention of the wolf away from the exhausted chased one). The compassionate behavior should eventually be discovered by the simulated evolution, provided that such a behavior confers a survival advantage to the team of caribou agents.

The obtained results suggest that the evolution of empathic agents is more efficient. Indeed, for the same computational effort of GP (i.e., the same number of generations), a higher number of successful situations is attained than for a team of non-empathic caribou agents. The average number of successful situations is significantly higher for the empathic caribou – eight vs. two – than in the team of non-empathic ones. Moreover, the evolved behavior of the empathic caribou agents is more effective as the evolution results yields a better escaping

5. Verifying the Survival Value of Swarming

5.1 Implementation of Swarming

In order to implement swarming behavior, we incorporated two additional features in the WCP – (i) the distance to the geometrical center of all the caribou that are seen by given caribou (ii) the bearing of this center, respectively. These two perceptions are implemented as two additional terminals in the set of terminal symbols of GP.

Thus, during the evolution, caribou agents were able to consider – in the conditional parts of the evolved IF-THEN behavioral rules – the distance or bearing (or both) to the center of the group of visible caribou agents. From another perspective, the center of the swarm could be considered as an additional, yet invisible (virtual) caribou with well-perceivable distance and bearing [13].

5.2 Evolution of Team of Empathic Caribou Agents without Swarming Behaviors

We conducted 20 independent runs of GP in an attempt to evolve a successful escape behavior in a team of eight empathic caribou agents without the implementation of swarming behavior. Within the considered context of the WCP, we viewed swarming behaviors as the ability of the caribou to understand in which direction it should move in order to become a part of (and thus seek help from) the closest group of caribou agents.

5.3 Evolution of a Team of Empathic Caribou Agents with Swarming Behavior

We conducted additional 20 runs of GP to evolve the successful escape behavior of a team of eight empathic caribou agents with swarming behavior. We implemented swarming behaviors by employing a well-perceived virtual caribou in the geometrical center of the group of visible caribou as mentioned in Subsection 5.1.

Figure 5 shows the convergence of the average number of successful situations for these two approaches. Figure 6 shows the results of statistical analysis using analysis of variance (ANOVA).
5.4 Discussion

As Fig. 5 illustrates, the dynamics of the improvement of the 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 somewhat faster than that of non-swarming ones, suggesting that the swarming contributes to the improvement of efficiency of evolution of the escape behavior while preserving its effectiveness.

Considering the concept of the ‘end of average’ [14], 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 was defined as the probability of achieving 90% of the desired result [9], 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 4 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 is not very significant, however, one could notice that the average number of generations required to achieve 9 (of 10) successful initial situations by the team of swarming agents (97.7) is about 10% lower than the analogical number of generations required for the team of caribou agents without swarming (108.9). Therefore, we could conclude that swarming contributes to the reduction of computational effort of evolution, and therefore – to the improvement of the computational efficiency of the latter.

6. The Dilemma between the Reactiveness and Proactiveness of the Behavior of Caribou Agents

6.1 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 [15]. Compared to the reactive agents, introduction of proactiveness 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 [16],[17]. 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 [18] or of engagements in unnecessary confrontations over shared resources.

In order to examine the effect of proactiveness on the efficiency of evolution or the effectiveness of the evolved behavior of caribou agents, we implemented a proactive architecture in the evolved Distraction (corresponding to the highest priority, social behavior) module of the latter. 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 proactively, regardless of the current perception information, as illustrated in Fig. 7. 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 proactiveness (with several behaviors being inserted into the queue) of the overall behavior of caribou agents.

Table 4 Comparative analysis of the features of evolutionary runs of GP during evolution of two types of caribou agents: without- and with swarming, 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 | 108.9           | 97.7         |

Fig. 6 Experimental results of ANOVA test.

Fig. 7 Time step-wise functionality of caribou agents.
ceived 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 reactivity) or multiple (in case of preponderance of proactiveness) 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 8 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;
```

Fig. 8 A human-readable representation of sample evolved IF-THEN behavioral rule.

As depicted in Fig. 8, 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 reactive and pro-active behavior in the caribou agents facilitates both efficiency of evolution and the effectiveness of their escape behavior.

6.3 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 setup were identical to those presented in previous sections of this article. The experimental results are summarized in Fig. 9. Figure 10 shows the results of statistical analysis using analysis of variance (ANOVA).

6.4 Discussion

As Fig. 9 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 situation 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.

Similarly to the comparative analysis conducted for the WCP in Section 4, 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 5 below. Being an obviously inferior, the results obtained from the evolution of purely reactive caribou agents (maxNB=1) are omitted from Table 5.

| Feature of the Evolutionary Runs | Value of maxNB |
|---------------------------------|----------------|
| 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 to 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 50 generations) | 144.9 | 191.4 | 192.7 |

As the results shown in Table 5 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 proactivity (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 proactivity (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 tradeoff between the reactivity and proactivity was achieved for maxNB=2, in that it results in the best possible efficiency of simulated evolution of the escape behavior of caribou agents.

We would like to summarize our finding that a limited proactivity 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 proactivity and reactivity in the escape behavior of caribou agents facilitates the achievement of the best results.

7. Conclusion

We introduced the WCP as a reversed instance of the well-studied predator-prey pursuit problem. Our problem was comprised of a team of caribou agents attempting to escape from a single yet superior (in terms of sensory abilities, raw speed, and maximum energy) wolf agent in a simulated two-dimensional infinite toroidal world. In the introduced WCP, we investigated whether socio-psychological aspects such as empathy, grouping (swarming), and the trade-off between reactivity and proactivity of the behaviors of caribou agents affect the efficiency of the simulated evolution of escape behavior or the effectiveness of such a behavior. We concluded that swarming improves the efficiency of evolution of caribou agents while preserving the effectiveness of their escape behavior. Finally, we investigated the dilemma between the reactivity and proactivity of the behaviors of caribou agents. The experimental results demonstrated that the trade-off between these two behaviors facilitates a significant improvement of efficiency of evolution and the effectiveness of the evolved escape behavior of the caribou agents. Moreover, the proposed approach of solving the dilemma between the reactivity and proactivity of the evolved behavior of entities – i.e., by varying the size of a FIFO-queue of commands executed under current perceptive conditions – is general enough to be employed for optimizing the behaviors of evolved (or coevolved) entities in the domains of multi-agent systems and evolutionary robotics.

As a logical continuation of our previous work solely dedicated to the effects of empathy on the efficiency of evolution of caribou agents in the WCP, in this work we focused on the effects of empathy, swarming, and resolution of the dilemma between reactivity and proactivity. We discovered two successful emergent behaviors of the caribou agents that result in a successful escape due to the physical exhaustion of the chasing wolf. One of these behaviors is the compassionate behavior of empathic caribou agents, which was seen in the voluntary movement of a caribou agent towards the chased one. The approaching caribou forces the wolf to change target from the currently chased (and, often exhausted) caribou to the newly approaching (physically stronger) one. The other discovered behavior was manifested in attracting the wolf from the currently chased (and exhausted) caribou by moving very slowly or even stopping. The emergent escape behaviors mentioned above could contribute to the physical exhaustion of the wolf agent by forcing the latter to switch its focus periodically to a stronger caribou and chase the latter in a longer and, therefore– sub-optimal zig-zag trajectory.

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