Evolving Game Strategy Through Diversity and Cooperation

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ABSTRACT

This paper describes an approach to the co-evolution of competing virtual creatures. Pairs of individuals enter one-on-one contests in which they contend to establish contact with a common resource. The individuals are subjected to a competitive fitness function. In each tournament one of the organisms implements a robust and cognition-based strategy. The second type of contestant genetically determines its game strategy. Interesting game strategy patterns are identified when this evolutionary process is simulated on populations. Furthermore these experiments show how strategic cooperation emerges to improve both individual and collective game performances.

KEY WORDS: Evolutionary computation, artificial life, GA, co-evolution.

1. INTRODUCTION

Interactions between evolving organisms are generally believed to have a strong influence on their resulting survival capabilities. Moreover, competition between organisms is thought to play a significant role in supporting evolutionary change. In a natural evolutionary system the success of an organism depends on many environmental factors including other organisms' performance. Unlike natural evolution, computational optimisation usually aims to search for individuals with the highest possible fitness values, where the fitness measure remains constant and depends only on the individual being tested.

The work presented here takes a closer look at an evolutionary phenomenon. In this case the fitness of an individual is highly dependent on the actions of its competing individuals. Organisms differentiated by their complexity participate in game tournaments. This type of experiments may allow us to address crucial questions. Can primitive virtual organisms, only acting under the influence of artificial selection, achieve more effective performances than those individuals of higher complexity?. Can strategic and developmental diversity provide the basis for some type of cooperation?. And finally, can this behaviour benefit both individual and collective performances?.

Co-evolution and competitive fitness are relevant to several artificial life environments such as *Verve* [1], *Tierra* [2] and *Bioland* [3]. Axelrod [4] and Kauffman [5] have made significant contributions to the analysis of coevolving systems in the context of the Iterated Prisoner's Dilemma and self-organization respectively. A number of co-evolution simulations in competing environments have been implemented [6]. For example Sims [7] reported a genetic algorithm approach to evolving 3D morphology and behaviour. The morphology of artificial creatures and their neural systems for controlling their movements are both genetically constructed. Thus, an unlimited hyperspace of possible morphological designs is obtained to produce interesting competition patterns. Angeline and Pollack [6], Hillis [8] and Reynolds [9] have also discussed competition and co-evolution to improve game performance. The research presented here deals with similar evolutionary problems, but differs in a number of key aspects. For example, this model involves two types of organisms, which are differentiated by their evolutionary history and cognitive capabilities. Another relevant aspect is the study of self-regulating cooperation to improve game performance. In the following section the game context and the digital creatures are described. Section 3 explains how an evolutionary approach was implemented. Section 4 shows the game performances and patterns observed. Finally Section 5 discusses the results and future research.

2. THE GAME AND THE CREATURES

Figure 1 depicts the environment in which two virtual organisms, *X* and *Y*, will compete to establish contact with a single source of energy. Each organism can either stay away from the source or approach it, without having any knowledge about the other organism's intentions. The competition is based on a binary decision code in which the organism morphology and physical dynamics

are not taken into account. This is done in order to focus on the strategic aspects of the game. Section 2.1 describes the organisms' design.

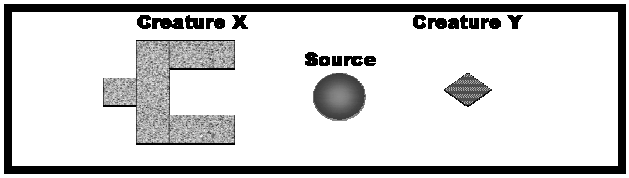

Figure 1. Two virtual organisms compete to have access to a source of energy.

In this game the winner of a contest is the organism with the highest score accumulated after a number of "moves". The highest score for a single move is obtained when only one of the creatures establishes contact with the source. But also each organism is interested in persuading its rival to stay away from the source. Therefore initially one may think that no matter what the other does, a selfish choice would produce the higher payoff. But if both decide to approach the source, both do worse than if both had been away from it. This hostile competition scenario can be observed in a natural ecosystem in which an organism would not take the risk of closely interacting with another creature. For example, each organism would care about the possibility of being attacked by the other creature when both try to approach the same source of energy. Figure 2 illustrates the four possible situations and the scores rewarded. Figures 2.a and 2.b show individual approaches to the source. Figure 2.c depicts a situation in which both individuals are rewarded 3 points for staying away from the source. This scenario may be less valuable than advancing near the source, but it is safer than doing it when the other creature has made the same decision (Figure 2.d).

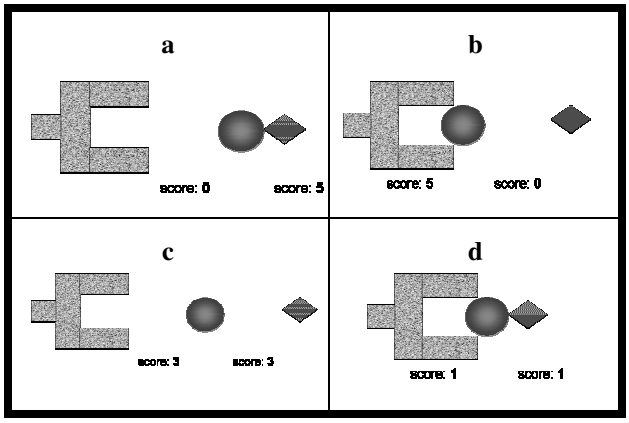

Figure 2. Competition scenarios. Panels 'a' and 'b' illustrate each of the creatures establishing contact with the source. Panel 'c', both creatures stay away from the source. Panel 'd', both creatures approach the source at the same time.

This game domain may also be interpreted as a *Prisoner's Dilemma* (PD) problem [10]. In the PD model two individuals can each either cooperate or defect. This model defines a payoff matrix similar to the score function shown in Figure 2. But unlike the studies published by Axelrod [6], the model reported here partially implements an iterated *Prisoner's Dilemma system* (IPD). A central feature in an IPD is the individual capacity to recognise previous rival or game moves.

2.1 ORGANISMS AND TOURNAMENTS

An artificial organism *Y* is represented by a genetic code that determines the sequence of moves during a contest against an artificial creature, *X*. Figure 3 illustrates an example, which consists of a binary string controlling 6 moves. Each bit value encodes one of the actions allowed in this game: "approach source" or "stay away from it". In the case depicted in Figure 3 the first action is "approach the source", and the last one is "stay away from it".

A creature *X* does not genetically define their game strategy. These individuals have developed basic cognitive and memory functions, such as the ability to remember some aspects of prior actions performed by the other contestant. Their strategy is based on the *Tit-for-Tat* strategy implemented in the computer tournaments organized by Axelrod [13]. In the current study this strategy is simply one of staying away from the source of energy on the first move, and then doing whatever the organism *Y* did on the preceding move. This strategy based on reciprocity has been chosen for its well-demonstrated robustness and adaptability [6]. Another important difference between these types of organisms is related to their evolutionary history. An organism *X* cannot modify its strategy during the execution of these tournaments. In biological terms one may say that the complexity of an organism *X* would require longer periods of time in order to evolve its strategic and recognition attributes. On the other hand, an organism *Y* might compensate the simplicity of its behavioral nature by evolving its genetic code from generation to generation. A summary of the differences between creatures *X* and *Y* is depicted in Figure 4.

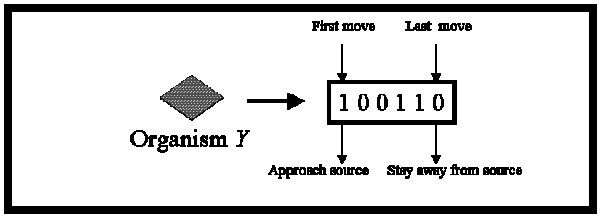

Figure 3. An artificial organism *Y* and its genetic code.

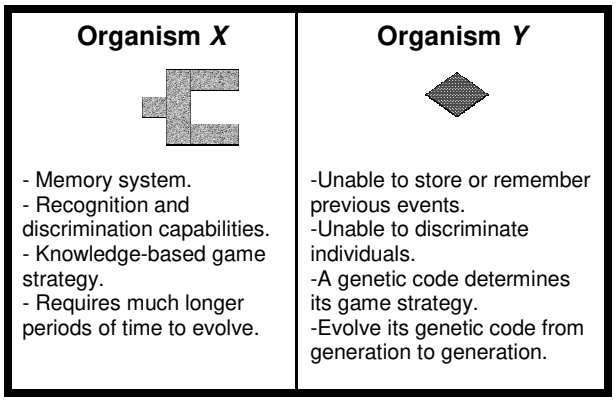

Figure 4. Summary of the differences between a creature *X* and an organism *Y*.

3. EVOLVING STRATEGY THROUGH A GA MODEL

A process of artificial selection is only performed on individuals *Y* as justified in the previous section. This process is based on a GA approach [11]. Initial populations are generated in a random fashion. The process of selection is achieved using rules of *mutation* and *reproduction*, which are illustrated in Figures 5.a and 5.b respectively. Mutation arbitrarily alters a string element of a selected genetic array by a random change with a probability equal to a mutation rate. The mechanism that actually selects the digit that is mutated is also based on a probabilistic scheme. Reproduction is performed to create two *offspring* genetic codes by swapping corresponding segments of the parents' codes. The procedures that decide the organisms to be reproduced, the matching couples and the dividing points in the parent genetic codes are also based on a probabilistic scheme.

In each generation, each organism *Y* enters a one-on-one contest against a creature *X*. The score obtained during a contest represents its fitness value, *F*. A number of organisms, *N*, will advance to the next generation if they are able to produce the highest scores among a population of *M* individuals from the current generation, where *M* is commonly greater than *N*. A user defines the value of *N* as well as the number of moves required to implement a contest. This process is repeated for a predefined number of generations or until an average fitness value has been achieved. Figure 6 summarises this evolutionary process.

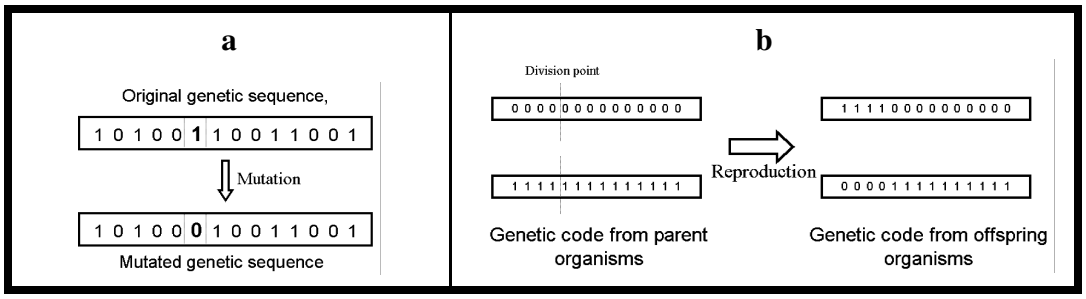

Figure 5. Genetic algorithm approach: **a.** mutation of a single organism *Y*; **b.** reproduction scheme.

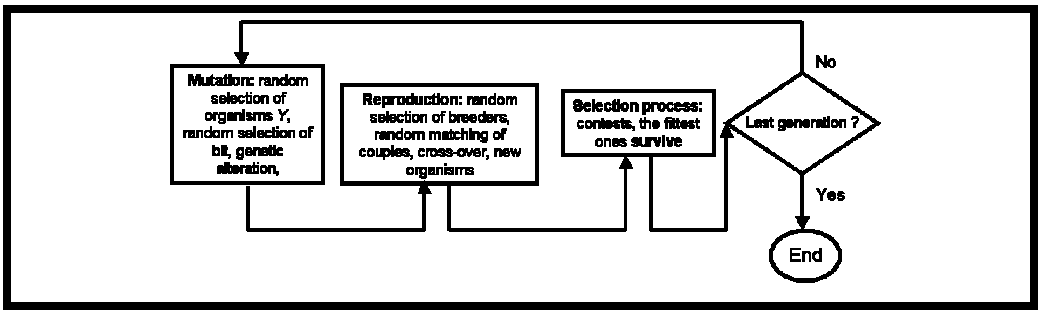

Figure 6. Evolving game strategy based on a GA model.

4. RESULTS

Figure 7 illustrates a contest simulation, which consists of 6 moves. These panels represent the sequence of actions executed by a creature *X* using a Tit-for-Tat strategy, and an organism *Y* performing a genetic strategy. The organism *Y*, which belongs to a fifth generation, won this contest. Figure 8 shows the genetic code used by the organism *Y*, and the resulting move sequence performed by the creature *X*. Arrows are used to depict the Tit-for-Tat strategy.

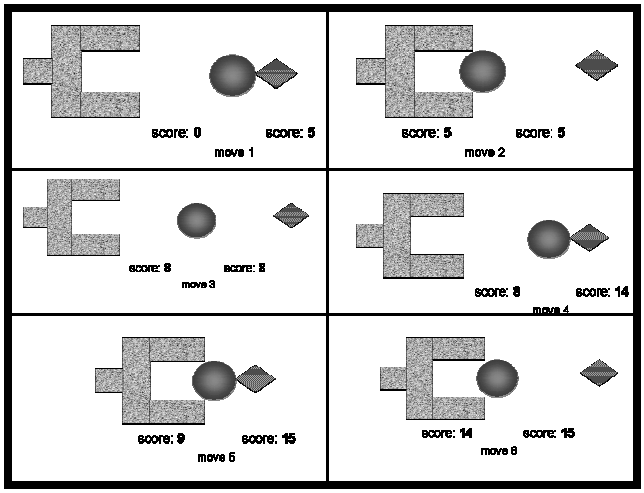

Figure 7. Contest simulation: an organism *X* performs a Tit-for-Tat strategy. Organism *Y* is a fifth generation individual that uses a genetically generated strategy.

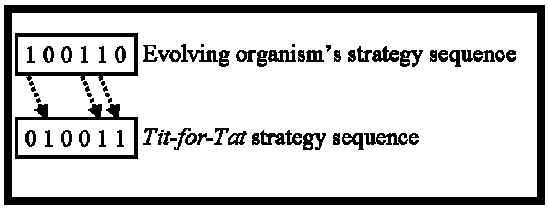

Figure 8. Sequence of actions performed in the contest illustrated in Figure 7.

Twenty-five independent populations of individuals *X* and *Y* performed competitions for a number of generations. Experiments using different mutation/reproduction rates and game lengths were also implemented. The performances of each generation from each population were monitored in order to analyse competition patterns. The results reported in this paper correspond to tournaments with a constant game length equal to 30, mutation rates equal to 0.01 and reproduction rates equal to 0.50. Random populations composed by 100 individuals from each type of organism were initially generated. Similarly, the 100 fittest individuals from each type of organism in the current generation were selected to be included in the next generation. Table 1 summarises the results of these tournaments performed by 25 independent populations during 20 generations. Organisms *Y* were able to win or draw all the individual games. Table 1 shows the average number of contests won by organisms *Y*, the number of drawn games, and their respective standard errors (S.E) for generations 1, 5, 10 and 20. After 20 generations organisms *X* were unable to win or draw any contest.

Table 1. Contests performed by 25 populations during 20 generations.

	Generation 1		**Generation 5**		**Generation 10**		**Generation 20**	
	W	D	W	D	W	D	W	D
Average	96.9	101.5	121.5	78.70	151.70	46	195.4	0
S.E	3.70	4.30	6.17	4.60	4.16	4.97	3.77	0

W: Contests won by organisms *Y;* D: Drawn contests; S.E: standard error.

A closer look at the results reveals the scoring pattern depicted by Figure 9. It shows the average scores as a function of time in a population of individuals *X* and *Y*. "Generation 0" refers to the initial population. Both types of organisms were able to incrementally improve their respective game performances.

The average differences are significant (t-tets, $P < 0.01$). Figure 9 also portrays the joint performances of individuals *X* and *Y*. Similar patterns were observed in the other populations examined in this study.

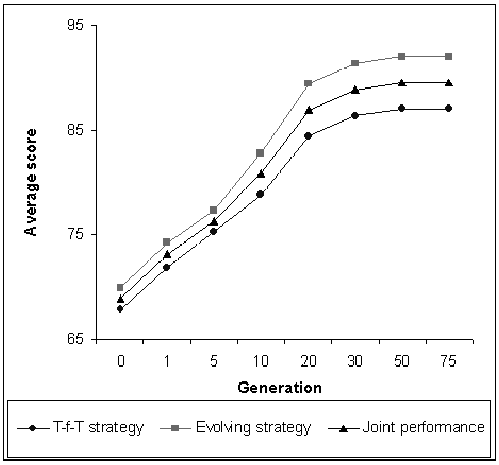

Figure 9. Summary of competition results: average scores of a population of individuals *X* (T-for-T strategy) and *Y* (evolving strategy) as a function of time.

The maximum individual scores produced by creatures *X* and *Y,* were equal to 87 and 92 respectively. These scores can be achieved in all the populations after 50 generations. The lowest individual and collective scores were obtained when an organism *Y* performed a random sequence of moves. Better individual and collective performances were produced when both creatures stayed away from the source. Successful organisms *Y* obtained the highest scores by breaking such a cooperation order just at the end of the competition.

5. DISCUSSION AND CONCLUSIONS

This paper reports a GA approach to co-evolution in a virtual environment. Diversity was achieved by defining individuals with distinct evolutionary and behavioural attributes. These results indicate that a variety of methods allow the organisms *Y* to outperform the Tit-for-Tat strategy implemented by the organisms *X*. The most interesting results occurred when the creatures were able to improve their scores by developing a *cooperation* policy. In this case cooperation was achieved when both individuals decided to stay away from the source and to avoid direct confrontation. One may argue that mature generations of organisms *Y* were successful due to their capacity to detect the advantages of game reciprocity. Organisms *X* incrementally improve their scores because of the well-known robustness of their game strategy [6],[13]. Thus these interaction and evolutionary patterns fostered the emergence of a productive collective performance. The game rules produced by evolving organisms *Y* resemble the Tit-for-Tat strategy. But it seems that their adaptation capabilities also allowed them to infer the best moment to develop a more selfish attitude. Such a moment is represented by the last move of the contest. This is a remarkable result since information about the length of the games was not provided to the creatures. The length of the competitions reported in this paper was equal to 30 moves, and an identical response was also observed in other simulations using different lengths.

Simulations containing larger number of species should be performed in order to explore other adaptation patterns. More realistic environments need to be simulated. In this way several creatures belonging to different species may compete and/or cooperate with each other, instead of performing one-on-one contests. It has been suggested that this type of systems may provide relevant insights into the study of natural ecosystems, video game design and biologically inspired machines [6], [12].

The results presented here suggest that digital organisms are able to outperform more complex species, detect patterns of reciprocity, evolve into cooperative groups and optimise solutions based on a simplified mechanism of evolutionary computation.

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