EVOLVING IMPROVED OPPONENT INTELLIGENCE

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ABSTRACT

Artificially intelligent opponents in commercial computer games are almost exclusively controlled by manually-designed scripts. With increasing game complexity, the scripts tend to become quite complex too. As a consequence they often contain "holes" that can be exploited by the human player. The research question addressed in this paper reads: How can evolutionary learning techniques be applied to improve the quality of opponent intelligence in commercial computer games? We study the off-line application of evolutionary learning to generate neural-network controlled opponents for a complex strategy game called PICOVERSE. The results show that the evolved opponents outperform a manually-scripted opponent. In addition, it is shown that evolved opponents are capable of identifying and exploiting holes in a scripted opponent. We conclude that evolutionary learning is potentially an effective tool to improve quality of opponent intelligence in commercial computer games.

INTRODUCTION

The aim of opponents in commercial computer games is to provide an entertaining playing experience rather than to defeat the human player at all costs. The quality of the opponent intelligence in games such as computer role-playing games (CRPGs), first-person shooters (FPSs) and strategy games, lies primarily in their ability to exhibit human-like behaviour. This implies that computer-controlled opponents should at least meet the following four requirements: (1) they should not cheat, (2) they should exploit the possibilities offered by the environment, (3) they should learn from mistakes, and (4) they should avoid clearly ineffective behaviour. Opponents in today's computer games, however, have not yet reached this level of behaviour. The appeal of massive online multi-player games stems partly from the fact that computer-controlled opponents often exhibit what has been called "artificial stupidity" (Schaeffer 2001) rather than artificial intelligence.

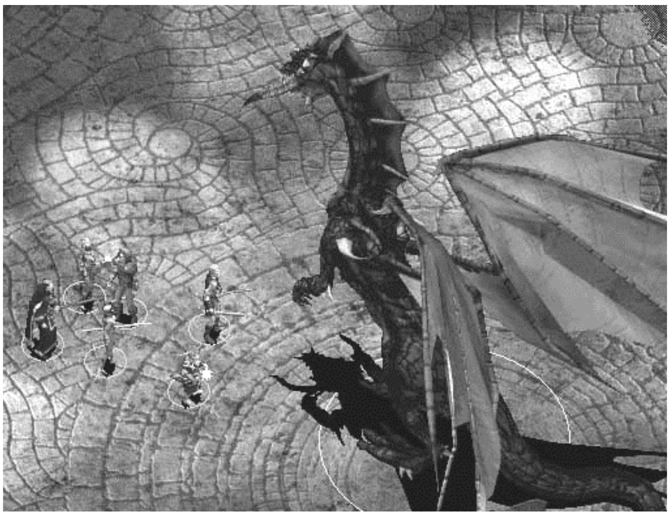

Figure 1: A dragon in SHADOWS OF AMN.

In early CRPGs and most of present-day FPSs and strategy games an opponent's behaviour is usually determined by a straightforward script such as "attack the target if it is in range, else move towards the target in a straight line." However, more advanced games contain opponents controlled by large scripts comprising hundreds of complex rules. As any programmer knows, complex programs are likely to contain bugs and unanticipated features. As a consequence, intelligent opponents intended to pose a considerable challenge to a human player often suffer from shortcomings that are easily recognised and exploited. For example, in the CRPG SHADOWS OF AMN (2000; illustrated in figure 1) the dragons, the supposedly toughest opponents in the game, could be easily defeated by taking advantage of holes in the extensive scripts controlling their actions. Evidently, such artificial stupidity spoils the playing experience.

State-of-the-art artificially intelligent opponents lack the ability to learn from experience. Therefore, the research question addressed in this paper reads: How can evolutionary learning techniques be applied to improve the quality of opponent intelligence in commercial computer games? We discuss two main ways of applying machine learning to games: off-line learning and on-line learning. We introduce the strategy game PICOVERSE and outline the duelling task for which we evolve opponent intelligence off-line. We then describe the environment and techniques we have used for our initial experiments. We present the results of our experiments and discuss them. Finally, we draw some conclusions and point out future research.

OPPONENT INTELLIGENCE LEARNING

We distinguish two main ways of applying machine learning to improve the quality of opponent intelligence in commercial computer games: on-line learning and off-line learning.

On-line Learning

Examples of on-line application of machine learning are some of the opponents developed for the popular FPS QUAKE. The artificial player in QUAKE III (commonly called a "bot") uses machine learning techniques to adapt to its environment and to select short-term and long-term goals

(Van Waveren and Rothkrantz 2001). John Laird has developed a bot that predicts player actions and uses these predictions to set ambushes and to avoid traps (Laird 2001). Of the four requirements we mentioned in the introduction for opponent strategies that exhibit high entertainment value, these bots address the first two, namely managing to avoid cheating and using their environment effectively. However, they can not learn from mistakes or generate completely new tactics to overcome ineffective behaviour. They mainly adapt to the world they find themselves in, rather than to the tactics of the human player. Still, these bots are a first step towards the creation of human-like opponents by on-line adaptation.

Machine learning techniques are rarely used in commercial computer games. Presumably, the widespread dissatisfaction of game developers with machine learning (Woodcock 2000) is caused by the bold aim of creating intelligent opponents using on-line learning. Machine learning techniques require numerous experiments, generate noisy results, and are computationally intensive. These characteristics make machine learning rather unsuitable for on-line adaptation of opponents in computer games.

Off-line Learning

In the off-line application of machine learning techniques the disadvantages mentioned for on-line learning do not pose an insurmountable problem. However, to our knowledge, developers of commercial games have never used machine learning for off-line learning. In our view the two main applications of off-line learning in games are: (1) to enhance intelligence of opponents by training them against other (scripted) opponents and (2) to proof opponents against unforeseen player tactics by detecting "holes" in the scripts controlling the opponents. The next three sections describe the experiments supporting our view on the off-line application of machine learning in games.

DUELLING SPACESHIPS

In our experiments, we apply off-line learning for optimising the performance of opponents in a strategy game called PICOVERSE. This section discusses the game and the learning task to be used in our experiments. Figure 2 shows three screenshots of the game. PICOVERSE is a relatively complex strategy game for the Palm (handheld) computer. Our intentions with the development of this game are twofold: (1) we use it to support and illustrate our views on the design of complex Palm games (Spronck and Van den Herik, 2002), and (2) in the present context, we use it to investigate the off-line application of machine learning to improve opponent intelligence.

In PICOVERSE the player assumes the role of an owner of a small spaceship in a huge galaxy. Players act by trading goods between planets, going on missions and seeking upgrades for their spaceship. During travel, players encounter other ships and combat may ensue. The ships are equipped with laser guns to fight opponent ships. They are protected from destruction by their hulls. Modelling ship damage, the strength of the hull decreases when hit by laser beams. The duels in PICOVERSE are more strategically oriented than action oriented. While the relative attack power and hull strengths of the spaceships are important factors in deciding the outcome of a fight, even overpowered players have a good chance to escape unharmed if their ship is equipped with fast and flexible drives or specific defence measures. To enhance immersiveness of the game, we permit opponents, who have access to the same equipment as the player, to escape from a duel that they are bound to lose, rather than to continue fighting until being destroyed. This feature makes the opponent intelligence non-trivial, despite the relatively low level of complexity of the game (as compared to state-of-the-art PC games).

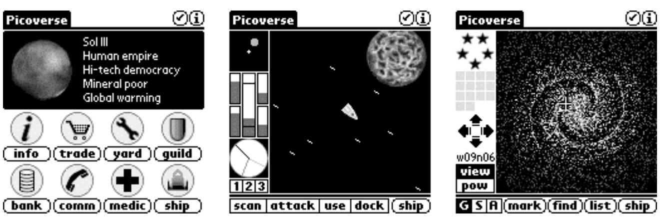

Figure 2: PICOVERSE.

OFF-LINE LEARNING EXPERIMENTS

In our experiments, the performance of a neural-network controlled spaceship is optimised using off-line learning in a simplified version of PICOVERSE. For both the evolved and opponent ships, lasers fire automatically when their enemy is within a certain range and within a 180-degree arc at the front of the ship. If a ship bumps head-on into the other ship, its speed is reduced to zero. The neural controllers are trained using evolutionary algorithms. The fitness is determined by letting the evolved spaceships combat against scripted opponents in a duelling task. Below, we discuss the duelling task, the neural network controlling the spaceship and the evolutionary algorithm.

The Duelling Task

Figure 3 is an illustration of the duelling task. We refer to the scripted ship as "the opponent" and to the ship that is controlled by a neural network as "the evolved ship". The scripted behaviour of the opponent is implemented as follows. The opponent starts by increasing its speed to maximum and rotating the ship's nose towards the centre of the evolved ship. While the opponent ship is firing its laser, it attempts to match its speed to the speed of the evolved ship. If the hull strength of the opponent is lower than that of the evolved ship, the opponent ship attempts to flee by turning around and flying away at maximum speed. This simple yet effective script mimics a basic strategy often used in commercial computer games.

The Neural Controller

The neural network controlling the (to be) evolved ship has ten inputs. Four inputs represent characteristics of the evolved ship: the laser power, the laser range, the hull strength, and the speed. Five inputs represent characteristics of the opponent ship: the location (direction and distance), current hull strength, flying direction, and speed. The tenth input is a random value. The network has two outputs, controlling the acceleration and rotation of the evolved ship. The hidden nodes in the network have a sigmoid activation

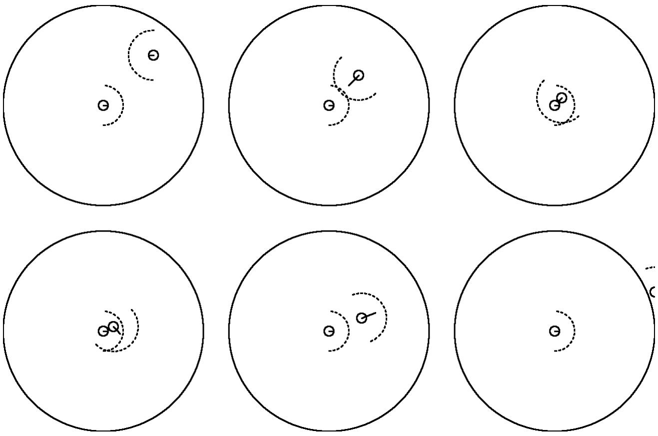

Figure 3: Sequence illustrating the duelling task. The duelling spaceships are represented by the small circles. A ship's direction is indicated by a line inside the circle, its speed by the length of the line extending from the ship's nose. The dotted arc indicates the laser range. The evolved ship is fixed to the centre of the screen and directed to the right. In the sequence the evolved ship is stationary. From left to right, top to bottom, the six pictures show the following events. (1) Starting position. (2) The opponent moves towards the evolved ship and (3) bumps into it. Both ships are firing their lasers. (4) The opponent has determined it should flee and turns around. (5) The opponent flees and (6) escapes.

function. The outputs of the network are scaled to ship-specific maximums.

We studied two types of neural networks, namely feedforward and recurrent networks. The feedforward networks include fully-connected networks (every neuron may be connected to any other neuron, as long as a feedforward flow through the network is guaranteed) and layered networks (neurons are only connected to neurons in the next layer). The recurrent neural networks are layered networks in which recurrent connections are only allowed between nodes within a layer. Recurrent connections function as a memory by propagating activation values from the previous cycle to the target neuron.

The Evolutionary Algorithm

An evolutionary system, implemented in the ELEGANCE simulation environment (Spronck and Kerckhoffs 1997), was used to determine the neural network connection weights and architecture. All simulations are based on the following settings: a population size of 200, an evolution run of 50 generations, real-valued weight encoding, size-2 tournament selection, elitism, Thierens' method of dealing with competing conventions (Thierens *et al.* 1993) and size-3 crowding. As genetic operators we used biased weight mutation (Montana and Davis 1989), nodes crossover (Montana and Davis 1989), node existence mutation (Spronck and Kerckhoffs 1997), connectivity mutation (Spronck and Kerckhoffs 1997), and uniform crossover. In addition, we added randomly generated new individuals to prevent premature convergence.

The fitness is defined as the average result of fifty duels between the evolved ship and its opponent. Each duel lasts fifty time steps. Each duel in which the ships started with different characteristics was followed by a duel in which the characteristics were reversed. At time step t the fitness is defined as:

$$Fitness_t = \begin{cases} 0 & PH_t \le 0 \\ \left(\dfrac{PH_t}{PH_0}\right) \Big/ \left(\dfrac{PH_t}{PH_0} + \dfrac{OH_t}{OH_0}\right) & PH_t > 0 \end{cases}$$

where PH_t is the hull strength of the evolved ship at time t and OH_t is the opponent hull strength at time t. The overall fitness for a duel is determined as the average of the fitness values at each time step.

Determining the fitness in this way has the following properties. If the evolved ship and its opponent both remain passive the fitness is equal to 0.5. If the opponent ship is damaged relatively more than the evolved ship, the fitness is larger than 0.5 and if the reverse is true (or when the evolved ship is destroyed) the fitness is smaller than 0.5. Therefore, the fitness function favours attacking if it leads to victory and favours fleeing otherwise.

RESULTS

Table 1 presents the results of the two types of networks tested in the experiments. Evidently, the layered feedforward neural networks with two layers outperforms all other networks in terms of average and maximum fitness value. The network with five nodes in each hidden layer scored only slightly better than the network with ten nodes in each layer.

At first glance the best fitness results achieved are not very impressive. A fitness of 0.5 means that the neural controller results are as effective as the manually-designed algorithm. A fitness of 0.579 (the best result obtained in the experiments) may be taken to indicate that the evolved opponent scores only slightly better than the scripted opponent. Since the scripted opponent employs a fairly straightforward tactic, one would expect the neural controller to be able to learn a far more successful tactic. However, a controller that remains passive reaches a fitness of 0.362. Given that a scripted

Neural network type	*Exps*	*Average*	*Lowest*	*Highest*
Recurrent, 1 layer, 5 hidden nodes	5	0.516	0.459	0.532
Recurrent, 1 layer, 10 hidden nodes	5	0.523	0.497	0.541
Recurrent, 2 layers, 5 nodes per layer	7	0.504	0.482	0.531
Feedforward, 7 hidden nodes	5	0.472	0.382	0.527
Feedforward, 2 layers, 5 nodes per layer	5	**0.541**	0.523	**0.579**
Feedforward, 2 layers, 10 nodes per layer	8	**0.537**	0.498	**0.576**
Feedforward, 3 layers, 5 nodes per layer	7	0.515	0.446	**0.574**

Table 1: Experimental results. From left to right, the columns indicate the type of neural network tested, the number of experiments performed with the neural network, the average fitness, the lowest fitness value and the highest fitness value. The best results are typed in boldface.

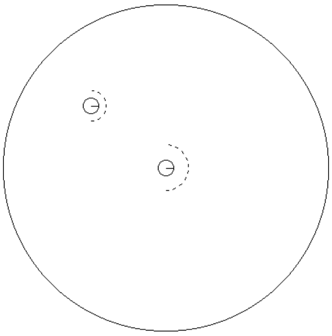

Figure 4: Opponent is behind the evolved ship.

opponent performs better than a stationary ship, a fitness of 0.638 is a theoretical upper bound to the maximum the neural controller can reach. From that point of view, a fitness of 0.579 is not bad at all.

From the perspective of playing experience, the fitness rating as calculated in our experiments is not as important as the objective result of a fight. A fight can end in victory, defeat, or a "draw". For the best controller, we found that 42% of the encounters ended in victory for the evolved ship, 28% in defeat, and 30% in a draw. This means that 72% of the encounters ended in a situation not disadvantageous to the evolved ship, which achieved 50% more victories than the opponent ship. Clearly, the evolved ship performs considerably better than the opponent ship.

DISCUSSION

Our results show that machine learning (i.e., off-line learning) can be used to create intelligent opponents that outperform scripted ones. Analysing the behaviour of the best-performing spaceship, we observed that it showed appropriate following behaviour when it overpowered the opponent. In these experiments, such following behaviour can never be detrimental to the performance. The reason for this is that the opponent's script ensures that it will only turn around to attack again if the hull strength of the attacker becomes less than its own hull strength, which does not happen as long as the evolved ship stays behind the opponent. As we expected the evolved ship avoided bumping against the opponent while following it. Avoiding bumping is appropriate behaviour because bumping reduces the evolved ship's speed to zero while leaving the opponent's speed unaffected, potentially allowing it to escape. However, contrary to our expectation the evolved ship did not avoid bumping by reducing its speed when approaching the opponent, but by swerving as much as needed to keep a constant relative distance to the opponent.

We further noticed that the evolved ship did not try to flee when losing a fight. The probable reason is that for a spaceship to flee, it must turn its back toward the enemy. The fleeing ship then becomes a target that does not have the ability to fight back (since lasers only fire from the front of the ship). As a result, fleeing ships are almost always destroyed before being able to escape. Such attempts to escape seem therefore of little use. From this observation we conclude that a better balance between the power of the weapons and the versatility of the ships is required to enable effective escape behaviour,.

Improving the Opponent

A surprising form of behaviour was observed when the opponent ship started behind the evolved ship, as illustrated in figure 4. In that case, often the evolved ship attempted to increase the distance between the two ships, up until the moment a draw would occur if it would continue to increase the distance. At that point, the evolved ship turned around and either repeated the behaviour or started to attack. Figure 5 illustrates this sequence of events.

An explanation for the success of the observed behaviour is that if the distance between the two ships is maximal, the evolved ship will have a maximal amount of time to turn around and face the opponent before it gets within the opponent's laser range. Since facing the opponent is required to counter-attack, the observed behaviour is beneficial to the evolved ship's strategy. Therefore, improving the script of the opponent accordingly may improve its quality considerably.

Detecting Shortcomings in the Script

By using off-line learning, we could also detect shortcomings in the scripted opponent. Although we did not specifically design our experiments for this purpose, we found a considerable hole in the script controlling the opponent by observing the behaviour of the two duelling ships.

The opponent bases its decision to flee on a comparison between the relative hull strengths (e.g., if the opponent's relative hull strength is lowest, it concludes that it will most likely lose the fight and will attempt to escape). The opponent's script does not take into account that it is its own turn to act when it makes this decision. If the comparative hull strengths are close to each other, this certainly becomes an important consideration. For instance, if on the initial approach the opponent ship came within the range of the lasers of the evolved ship before being able to fire its own lasers, it would be damaged while the evolved ship would still be undamaged. Regardless of its own power, this would cause the opponent's initial reaction to be to flee. Since in most cases the opponent would still be able to fire its lasers once, this behaviour had little influence if the opponent significantly overpowered the evolved ship, because it would start to attack again on the next turn. However, if the strengths of the ships were about equal, we found the evolved ship to exploit this weakness of the opponent, by attempting to manoeuvre into a position from which it could fire the first

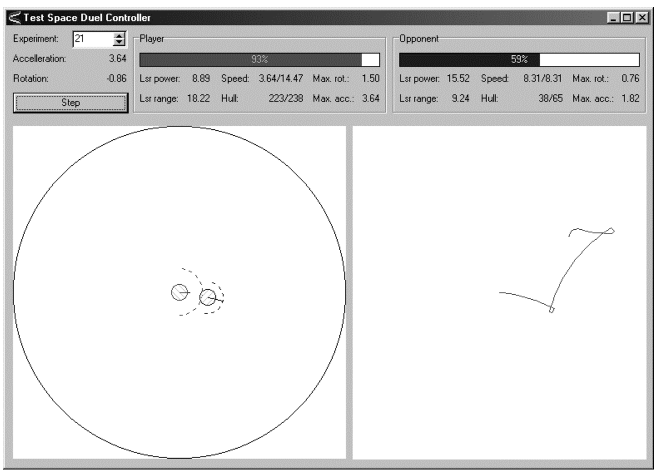

Figure 5: The right panel displays a trace of the movements of the evolved ship up to the moment that it fires its first shot. The opponent is overpowered and tries to flee, but the learning ship follows, as shown in the left panel. In this case the opponent is not able to escape.

shot. Plugging this hole in the opponent's script will be a major improvement to its behaviour.

It is noteworthy that in many commercial turn-based games we have observed holes in the opponent AI similar to the hole we discovered in our script. For instance, in many games it is a good tactic for the player to pass game turns until the enemy has approached to a certain distance so that the player can initiate the first attack. Game designers will seldom let computer opponents employ such a tactic because it could lead to a stalemate where both the player and the computer refuse to move, because whoever makes the first move is at a disadvantage. Similarities with trench warfare are striking.

Generalisation to Other Games

We have shown how machine learning can be used to improve opponent intelligence in PICOVERSE. Of course, it remains an open question whether our findings generalise to the far more complex commercial PC games. Even the detection of holes in scripted AI, which is obviously much simpler than developing a whole new tactic, may prove to be too difficult if the number of choices at each turn and the number of turns in an encounter are very large. However, we expect for most games that encounters do not last "too long" (to avoid boredom) and the number of choices is not "too large" (to avoid confusion). Even for commercial PC games it should therefore usually be possible to detect AI shortcomings by machine learning.

Employing machine learning to design completely new tactics, however, is probably severely limited in its uses. John Laird warns that while neural networks and evolutionary systems may be applied to tune parameters, they are "grossly inadequate when it comes to creating synthetic characters with complex behaviours automatically from scratch" (Laird 2000). For a relatively simple game as PICOVERSE machine learning techniques by themselves can be useful in designing strong tactics. The combination of machine learning with more structured techniques, such as a subsumption architecture (Brooks 1991) or a technique inspired by Laird's Soar Quakebot (Laird 2001), is likely to lead to more reliable good results within a shorter time, and may therefore also be suitable for more complex environments.

CONCLUSIONS AND FUTURE WORK

By applying off-line learning in the computer strategy game PICOVERSE we were able to improve opponent intelligence and to detect shortcomings in the scripted opponent. We conclude that machine learning can be applied off-line to improve the quality of opponent intelligence in commercial computer games. We expect the application of off-line learning to detect holes in commercial computer game scripts to be feasible.

Our future research will build upon our results with PICOVERSE. The release version of PICOVERSE will be more complex than the simulation we used, and we will run similar experiments on the more complex opponents in that version. For creating new opponent tactics, we intend to explore other machine learning techniques in combination with, for instance, subsumption architectures. In the long run, we hope to apply our techniques to improve opponent intelligence in commercial computer games.

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ELEGANCE is available from http://www.cs.unimaas.nl/p.spronck/.

PICOVERSE is targeted for a release early 2003 and available from http://www.picoverse.com/.