Imitation-Based Evolution of Artificial Players in Modern Computer Games

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ABSTRACT

Because of the rapid progress of commercial computer games in recent years the development of artificial characters that inhabit the presented game worlds has become a challenging task with very specific requirements. A very important feature of artificial intelligence for games is that, as the objective of computer games is the entertainment of the player, the artificial game agents should not only be competitive but also show intelligent and human-like behaviours. Therefore, this paper proposes the usage of imitation techniques to generate more human-like behaviours in an action game, whereas the imitation is achieved by recording players and by using these recordings as the basis of an evolutionary learning approach.

Track: Genetics-Based Machine Learning and Learning Classifier Systems

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1. INTRODUCTION

Many modern computer games feature very complex and highly dynamic virtual worlds with realistic physics. However, the artificial intelligence routines of the characters that inhabit these game worlds - usually called game AI - is often static and relies on pre-written scripts [1]. Scientific research in the area of game AI has therefore concentrated on the deployment of learning methods to create competitive agents - often with very high performing results [2, 3].

However, creating game AI for a real game should also have the goal to create more entertaining and believable game agents. Therefore, gaming characters should not be as good as possible or be almost invincible. They should show some sophisticated human-like behaviours. For example in an action game, the agents should not just aggressively try to inflict as much damage as possible. It is much more desirable that they try to use the map structure for taking cover or try to trick their opponents.

The question is how such a behaviour can be achieved. In our opinion, a pure learning approach based on the optimisation of behaviour is inappropriate because it usually just optimises the raw performance of the game agents. We argue that to behave human-like, an agent should base its behaviour on how human players play the game and try to imitate them. This should especially be the case in computer games in which human and artificial players meet at the same level and where it is quite simple to record the behaviour of a human player.

However, a raw imitation of other players is usually not able to generate competitive performance. The reason for this lies in inherent errors that are made in the imitation process - e.g. by assuming a certain state and action model - that usually deteriorate the performance of the imitator. Therefore, we propose to devise an optimisation method on top of a representation that is based on recorded player behaviour to obtain competitive and imitating agents.

This paper presents an imitation-based approach that uses an evolutionary algorithm as the additional optimisation method, to successfully train imitating agents for combat in QUAKE III (©1999, id software) - a popular three-dimensional action game. It is based on an evolutionary learning approach that we have published in 2006 [6]. However, in this case, the evolutionary process is mainly not used to create new knowledge, but to select the right combination of imitated behaviour pieces and to smooth the resulting behaviour. Though we have already published the basic concept of the presented imitation approach in 2005 [5], this paper presents a more refined method and more results on its application.

2. IMITATION-BASED LEARNING

To achieve imitation, the approach uses the recording of some player. This recording contains state to action matches, whereas the states are encoded as a grid of quadratic regions that cover the vicinity of the observed player and that are aligned relatively to the view direction of the observed player (see figure 1). The actions are just the movement commands - e.g. go forward, left and turn by some degrees. These matches are recorded 10 times per second.

The imitating agents also use the same state and action model for the encoding of their behaviour. Each agent is controlled by a list of rules which map states to fitting actions. These rules are initialised with random state to action matches from a recording which is the basis for the desired imitation.

The evolutionary algorithm that tries to optimise the rule lists basically uses a population of game agents to breed well performing ones. The performance and fitness of an agent is computed from the damage the agent applied to its opponents minus the damage

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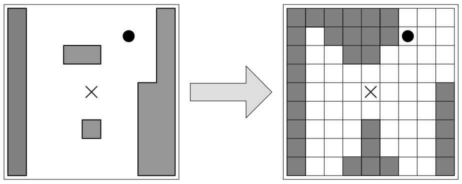

Figure 1: Grid Computation

that it received over a certain timespan. In our experiments we evaluate each agent for one minute by playing against the built-in QUAKE III agent because it presents a constant opponent that can be used as a benchmark. In addition, the experiments also use the QUAKE III agent as the imitation source because this makes it possible to see, if the imitating agents can become competitive. In addition, the QUAKE III agents show a very distinctive behaviour that helps to judge the quality of the show imitation.

Concerning the evolutionary operators, recombination is achieved by uniform crossover between two rule lists. Only mutation can change the structure of the rules themselves by adding small changes to the proposed movement commands. We assume, that the recording already contains all important states and, therefore, apply no mutation on the grids. Selection works according to a (10+50) selection scheme. We keep the parents in the population to better cope with the uncertain fitness function.

3. RESULTS

In the following we will shortly state the most important results of the extensive experiments that we have conducted. For a detailled analysis we refer to [4]. Figure 2 shows the mean and maximum performance of each generation in the best parameter setup, averaged over 20 runs. A performance of 0 means that the agent has inflicted about the same damage as it has received. Therefore, the agents in the population becomes in average as good as their opponents and role models. The best individuals are able to reliably defeat their opponent.

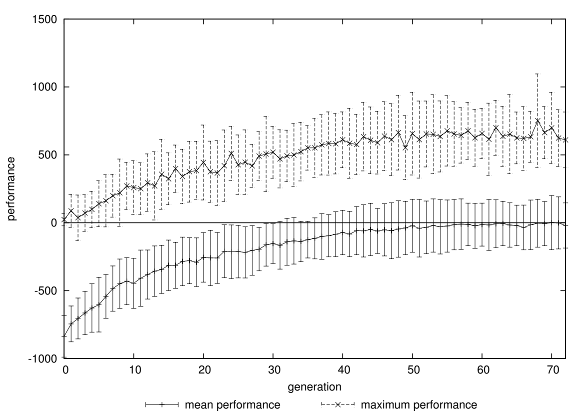

Figure 2: Results of the best Setup

The striking result of the experiments is that the imitation-based initialisation has a strong effect on the performance and the behaviour of the evolved agents. The reached maximum performance is considerably lower than the results of the pure evolution[1] in [6].

[1]The best agents reached a performance of above 2500

Therefore, the evolution of competitive behaviour when starting from an imitation rule base seems to be a harder problem. However, it should be expected that the performance of an imitating agent is closer to the level of its role model.

Concerning the gaming behaviour of the agents, the result is that they very closely imitated the QUAKE III agents[2] In the first generations the right combination of rules had to be sorted out and the agents behaved quite randomly. Though, they already showed a much more valid gaming behaviour as a randomly initialised agent. Then - beginning with approximately the fifth generation - the agents started to closely mirror the QUAKE III agent in its movements. Later, in the course of the evolution, the agents took more and more freedom in their movements. For example, some agents started to take cover behind a wall while their weapon reloaded. This behaviour was not present in the rule base and represents a level of sophistication in the learnt behaviour that was not shown by our previous pure learning approach [6].

The presented system can be used to train certain aspects of the behaviour of an artificial opponent based on the imitation of other players. If an agent should show a certain behaviour, the usage of imitation will allow it to just demonstrate the desired behaviour. Our approach has also turned out to prevent disadvantageous behaviours, because they impair the fitness of the agent. Such behaviours, e.g. getting stuck in corners or standing still, have been eliminated in all experiments after at most 20 to 30 generations. The generated agents, though having a lower performance, showed a much higher level of sophistication in their behaviour and appeared much more human-like as the agents that were generated by using plain evolution [6]. However, it should be noted that the presented approach is only able to base its results on the imitation of the respective role model but not to fully imitate it because of the added rule optimisation. Therefore, the imitating agents will always only imitate the behaviours that have proven to be useful. In addition, the method can not be applied to an online scenario in an ongoing game because it often generates defective agents which compromises the gaming experience. To achieve this more cautious variation operators would be needed.

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[2]See `https://chaos.cs.upb.de/imitation.avi.` for a demonstration.