Interesting Games through Stage Complexity and Topology

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1. Problem Statement

In (Yannakakis and Hallam, 2004) we saw that the on-line learning (OLL) mechanism proposed is a robust approach which manages to emerge opponents (i.e *Ghosts*) that increase the interest of the prey-predator, multi-agent Pac-Man computer game. It also demonstrated high adaptability to changing types of *Pac-Man* player (i.e. playing strategies) in a relevantly simple playing stage.

In the work presented here we attempt to test the OLL mechanism over more complex stages and furthermore to explore the relation between the interest measure and the topology of the stage. In order to distinguish between stages of different complexity, we require an appropriate measure to quantify this feature of the stage. This measure is as follows

$$C = 1/E\{L\} \tag{1}$$

where C is the complexity measure and $E\{L\}$ is the average corridor length of the stage.

According to (1), complexity is inversely proportional to the average corridor length of the stage. That is, the longer the average corridor length, the easier for the *Ghosts* to block *Pac-Man* and, therefore, the less complex the stage.

Figure 1 illustrates the four different stages used for the experiments presented here. Complexity measure values for the Easy A, Easy B, Normal and Hard stages are 0.16, 0.16, 0.22 and 0.98 respectively. Easy A stage is the test-bed used in (Yannakakis and Hallam, 2004). Furthermore, given that a) blocks of walls should be included b) corridors should be 1 grid-square wide and c) dead ends should be absent, Hard stage is the most complex Pac-Man stage for the *Ghosts* to play.

Stages of the same complexity, measured by (1), can differ in topology (i.e. layout of blocks on the stage). Thus, in the case of Easy A and Easy B (see figure 1), stages have the same complexity value but are topologically different.

The choice of these four stages is made so as to examine the on-line learning mechanism's ability to emerge interesting opponents in stages of different complexity or equally complex stages of different topology. Results presented in section 2 show that the mechanism's efficiency is independent of both the stage complexity and stage topology and, furthermore, illustrate the approach's increasing generality on the game.

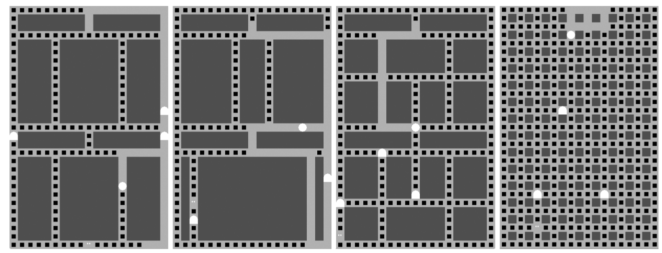

Figure 1: The 4 different stages of the game. Increasing complexity from left to right: Easy (A and B), Normal and Hard.

2. Results

Off-line trained (OLT) emergent solutions are the OLL mechanisms' initial points in the search for more interesting games. The OLL experiment is described as follows. a) Pick nine different emerged *Ghosts'* behaviors produced from off-line learning experiments — Blocking (B), Aggressive (A) and Hybrid (H) behaviors emerged by playing against each of 3 *PacMan* types (i.e. Cost-Based (CB), Rule-Based (RB) and Advanced (ADV) players) — for each one of the three stages; b) starting from each OLT behavior, apply the OLL mechanism by playing against the same type of *PacMan* player and in the same stage the *Ghosts* have been trained in off-line. Initial behaviors for the Easy B stage are OLT behaviors emerged from the Easy A stage. This experiment intends to demonstrate the effect of the topology of a stage in the interest of the game; c) calculate the interest of the game every 100 games during each OLL attempt.

In order to calculate the interest, we let the *Ghosts* play 100 non-evolution games in the same stage against the *PacMan* type they were playing against during OLL.

We need to minimize the non-deterministic effect of the *PacMan's* strategy on the game's interest and therefore, we use a uniform random distribution to pick 10 different 50-tuples out of these 100 games. These 10 samples of data, of 50 games each, are used to determine the games' average as well as confidence interval values of interest. The outcome of this experiment is presented in Table 1 and Figure 2.

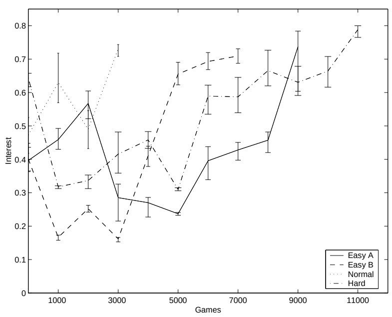

Figure 2: On-line learning effect on interest of ADV Hybrid initial behavior in all four stages

Since we have 3 types of players, 3 initial OLT behaviors and 4 stages, the total number of different OLL experiments is 36. These experiments illustrate the overall picture of the mechanism's effectiveness over the complexity and the topology of the stage as well as the *PacMan* types and the initial behavior. Due to space considerations we present only 4 (see Figure 2) out of the 36 experiments here, where the evolution of interest over the OLL games (starting from the hybrid behavior emerged by playing against the ADV *Pac-Man* player) on each stage is illustrated.

As seen from Figure 2, the OLL mechanism manages to find ways of increasing the interest of the game regardless the stage complexity or topology. In all 36 OLL experiments the learning mechanism was capable of producing games of higher than the initial interest as well as maintaining that high interest for a long period.

It is obvious that a number of the order of 10^3 constitutes an unrealistic number of games for a human player to play. In other words, it is very unlikely for a human player to play so many games in order to see the game's interest increasing. The reason for the OLL process being that slow is a matter of keeping the right balance between the process' speed and its 'smoothness' (by 'smoothness' we mean the interest's magnitude of change over the games). A solution to this problem is to consider the initial long period of disruption as an off-line learning procedure and start playing as soon as the game's interest increases.

Table 1 presents the best average interest values obtained from the OLL mechanism. It is clear that the OLL approach constitutes a robust mechanism that, starting from suboptimal OLT *Ghosts*, manages to emerge interesting games (i.e. interesting *Ghosts*) in the majority of cases (i.e. in 16 out of 27 cases $I > 0.75$). It is worth mentioning that in 15 out of 27 different OLL attempts the best interest value is greater than the respective Follower's value.

Furthermore, in nearby all cases, the interest measure is kept at the same level independently of stage complexity or — in the case of Easy A and B stages — stage topology. Given the confidence intervals (maximum of ± 0.05, ± 0.03 on average) of the best interest values, it is shown that the emergent interest is not significantly different from stage to stage.

			Play Against		
		Stage	CB	RB	ADV
Fixed Behaviors	R	Easy A	0.5862	0.6054	0.5201
		Easy B	0.5831	0.5607	0.4604
		Normal	0.5468	0.5865	0.5231
		Hard	0.3907	0.3906	0.3884
	F	Easy A	0.7846	0.7756	0.7759
		Easy B	0.7072	0.6958	0.6822
		Normal	0.7848	0.8016	0.7727
		Hard	0.7727	0.7548	0.7627
	O	Easy A	0.6836	0.7198	0.6783
		Easy B	0.6491	0.6725	0.6337
		Normal	0.7297	0.7490	0.6855
		Hard	0.6922	0.7113	0.4927
Off-Line Trained	B	Easy A	0.8195	0.7713	0.5667
		Easy B	0.7636	0.7472	0.6619
		Normal	0.7804	0.7694	0.6858
		Hard	0.7394	0.7568	0.7463
	A	Easy A	0.7967	0.7184	0.7630
		Easy B	0.7685	0.7368	0.7432
		Normal	0.7539	0.7416	0.8023
		Hard	0.7245	0.7175	0.7375
	H	Easy A	0.7622	0.8228	0.7374
		Easy B	0.7723	0.7492	0.7094
		Normal	0.7484	0.7265	0.7309
		Hard	0.7426	0.7624	0.7833

Table 1: Best interest values achieved from on-line learning on *Ghosts* trained off-line (B, A, H). Fixed strategy *Ghosts'* — Random (R): untrained *Ghosts*; Followers (F): *Ghosts* designed to follow *PacMan* constantly and move so as to reduce the greatest of their relative distances from *PacMan*; Near-Optimal (O): a *Ghost* strategy designed to produce attractive forces between *Ghosts* and *PacMan* as well as repulsive forces among the *Ghosts* — interest values are presented for comparison. Values are obtained by averaging 10 samples of 50 games each.

References

Yannakakis, G. N. and Hallam, J. (2004). Evolving Opponents for Interesting Interactive Computer Games. To Appear in Proceedings of the 8^{th} International Conference on Simulation of Adaptive Behavior.