A Scheme for Creating Digital Entertainment with Substance

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Abstract

Computer games constitute a major branch of the entertainment industry nowadays. The financial and research potentials of making games more appealing (or else more interesting) are more than impressive. Interactive and cooperative characters can generate more realism in games and satisfaction for the player. Moreover, on-line (while play) machine learning techniques are able to produce characters with intelligent capabilities useful to any game's context. On that basis, richer human-machine interaction through real-time entertainment, player and emotional modeling may provide means for effective adjustment of the non-player characters' behavior in order to obtain games of substantial entertainment. This paper introduces a research scheme for creating NPCs that generate entertaining games which is based interdisciplinary on the aforementioned areas of research and is foundationally supported by several pilot studies on testbed games. Previous work and recent results are presented within this framework.

1 Introduction

While game development has been concentrated primarily on the graphical representation of the game worlds, minor focus has been given to non-player characters' (NPCs') behavior. Simple scripted rules and finite-state or fuzzy-state machines are still used to control NPCs in the majority of games [Woodcock, 2001; Cass, 2002]. The increasing number of multi-player online games (among others) is an indication that humans seek more intelligent opponents and richer interactivity. Advanced artificial intelligence techniques are able to improve gaming experience by generating intelligent interactive characters and furthermore cover this human demand [Funge, 2004]. Moreover, computational power may bring expensive innovative AI techniques such as machine learning to meet a game application in the near future.

Game players seek continually for more enjoyable games as they spent 3.7 days per week playing an average of 2.01 hours per day [Rep, 2002], as stressed in [Fogel *et al.*, 2004], and this interest should somehow be maintained. It is only very recently that game industry has begun to realize the great (financial) importance of stronger AI in their products. Boon [2002] stresses that the most common complaint that gamers have is that the game is too short. However, as Boon claims, rather than making games longer game developers should focus on making games more interesting and appealing to both hard-core and soft-core gamers.

Intelligent interactive opponents can provide more enjoyment to a vast gaming community of constant demand for more realistic, challenging and meaningful entertainment [Fogel *et al.*, 2004]. However, given the current state-of-the-art in AI in games, it is unclear which features of any game contribute to the satisfaction of its players, and thus it is also uncertain how to develop enjoyable games. Because of this lack of knowledge, most commercial and academic research in this area is fundamentally incomplete.

In this paper, a general scheme for obtaining digital entertainment of richer interactivity and higher satisfaction is presented. On that basis, previous achievements within this framework are outlined and new promising results that reinforce our intentions are portrayed. The challenges we consider within the proposed scheme are to provide qualitative means for distinguishing a game's enjoyment value and to develop efficient tools to automatically generate entertainment for the player. In that sense, investigation of the factors/criteria that map to real-time enjoyment for the player as well as the mechanisms that are capable of generating highly entertaining games constitute our primary aims. The levels of human-game interaction that we consider in this work are focused on the player's actions and basic emotions and their impact to the behavior of the NPCs.

2 Related Work

This section presents a literature review on the interdisciplinary research fields that the proposed scheme attempts to combine. These include entertainment metrics for computer games; on-line adaptive learning approaches; user modeling and player's emotional flow analysis in computer games.

2.1 Entertainment metrics

Researchers in the AI in computer games field are based on several empirical assumptions about human cognition and human-machine interaction. Their primary hypothesis is that by generating human-like opponents [Freed *et al.*, 2000], computer games become more appealing and enjoyable. While there are indications to support such a hypothesis (e.g. the vast number of multi-player on-line games played daily on the web) and recent research endeavors to investigate the correlation between believability of NPCs and satisfaction of the player [Taatgen *et al.*, 2003], there has been no evidence that a specific opponent behavior generates more or less interesting games.

Iida's work on measures of entertainment in board games was the first attempt in this area. He introduced a general metric of entertainment for variants of chess games depending on average game length and possible moves [Iida *et al.*, 2003]. On that basis, some endeavors towards the criteria that collectively make simple online games appealing are discussed in [Crispini, 2003]. The human survey-based outcome of this work presents challenge, diversity and unpredictability as primary criteria for enjoyable opponent behaviors.

2.2 On-Line Adaptive Learning

There is a long debate on which form of learning is the most appropriate and feasible for a computer game application. In between off-line and on-line learning, the latter can be slow and lead to undesired and unrealistic behavior but it can demonstrate adaptive behaviors. Off-line learning is more reliable but it generally generates predictable behaviors [Manslow, 2002; Champandard, 2004]. However, researchers have shown that on-line learning in computer games is feasible through careful design and efficient learning methodology [Demasi and de O. Cruz, 2002; Johnson, 2004; Ponsen and Spronck, 2004; Stanley *et al.*, 2005].

2.3 User Modeling in Computer Games

Player modeling in computer games and its beneficial outcomes have recently attracted the interest of a small but growing community of researchers and game developers. Houlette's [2004] and Charles' and Black's [2004] work on dynamic player modeling and its adaptive abilities in video games constitute representative examples in the field. According to [Houlette, 2004], the primary reason why player modeling is necessary in computer games is in order to recognize the type of player and allow the game to adapt to the needs of the player. Many researchers have recently applied such probabilistic network techniques for player modeling on card [Korb *et al.*, 1999] or board games ([Vomlel, 2004] among others) in order to obtain adaptive opponent behaviors.

2.4 Real-time Emotional Flow

For modeling the player's emotions real-time, we gain inspiration primarily from the work of Kaiser et al. [1998]. They attempted to analyze emotional episodes, facial expressions and feelings — according to the Facial Coding Action System [Eckman, 1979] — of humans playing a predator/prey computer game similar to Pac-Man [Kaiser and Wehrle, 1996].

3 The Scheme

As previously mentioned, given the current state-of-the-art in AI in games, it is unclear which features of any game contribute to the enjoyment of its players, and thus it is also doubtful how to generate enjoyable games. Research endeavors aiming to do this without clear understanding of what factors yield enjoyable gaming experience will inevitably be unsuccessful.

In order to bridge the current gap between human designation of entertainment and interest generated by computer games and to find efficient and robust paths in obtaining appealing games, there is a need for an intensive and interdisciplinary research within the areas of AI, human-computer interaction and emotional and cognitive psychology. We therefore aim at exploring the novel directions opened by previous work on introducing entertainment measurements and adaptive on-line learning tools for generating interesting computer games [Yannakakis and Hallam, 2004a; 2005b]. The long-term target of this work is to reveal the direct correlation between the player's perceived entertainment (I), his/her playing strategy (style) (U) and his/her emotional state (E) — see Figure 1. Such a perspective will give insights into how a game should adapt to and interact with humans, given their emotional state and playing skills, in order to generate high entertainment. Towards this purpose, an innovative computer game will be developed, based on an interactive system that will allow one to study the ongoing processes of situated game state, the user's playing style and emotional flow.

The steps towards meeting our objectives are described in the following sections (see Figure 1). Previous and recent research achievements at each part of the proposed scheme are also presented.

4 Enjoyable Cooperative Opponents

Cooperation among multiple game characters portrays intelligent behavior and exhibits more enjoyment for the player. From that perspective, teamwork is a desired gaming opponent behavior. We therefore experiment with games of multiple opponents where cooperative behaviors could be generated and studied.

A set of games that collectively embodies all the above-mentioned environment features is the predator/prey genre. We choose predator/prey games as the initial genre of our game research [Yannakakis *et al.*, 2004; Yannakakis and Hallam, 2004a] since, given our aims, they provide us with unique properties. In such games we can deliberately abstract the environment and concentrate on the characters' behavior. The examined behavior is cooperative since cooperation is a prerequisite for effective hunting behaviors. Furthermore, we are able to easily control a learning process through on-line interaction. In other words, predator/prey games offer a well-suited arena for initial steps in studying cooperative behaviors generated by interactive on-line learning mechanisms. Other genres of game (e.g. first person shooters) offer similar properties and will be studied later so as to demonstrate the methodology's generality over different genres of game.

4.1 Interest Metric

In order to find an objective measure of real-time entertainment (i.e. interest) in computer games we first need to empirically define the criteria that make a specific game interesting. Then, second, we need to quantify and combine all

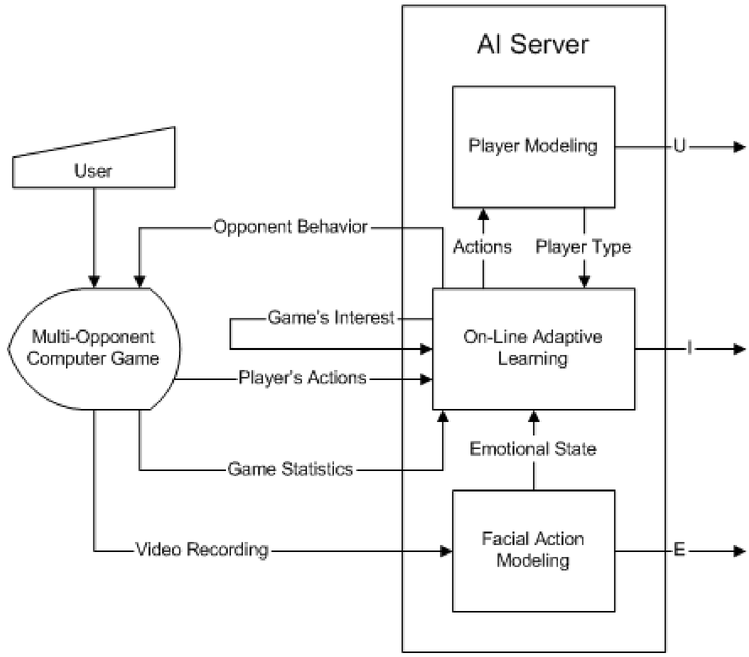

Figure 1: The proposed scheme.

these criteria in a mathematical formula. Subsequently, test-bed games should be tested by human players to have this formulation of interest cross-validated against the interest the game produces in real conditions. To simplify this procedure we will ignore the graphics' and the sound effects' contributions to the interest of the game and we will concentrate on the opponents' behaviors. That is because, we believe, the computer-guided opponent character contributes the vast majority of qualitative features that make a computer game interesting. The player, however, may contribute to its entertainment through its interaction with the opponents of the game and, therefore, it is implicitly included in the interest formulation presented here.

In [Yannakakis and Hallam, 2004a], we introduced the criteria that collectively define entertainment in predator /prey games. According to these criteria a game is interesting when: a) it is neither easy nor difficult to play; b) the opponents' behavior is diverse over the game and c) the opponents appear as they attempt to accomplish their predator task via uniformly covering the game environment. The metrics for the above-mentioned criteria are given by T (difference between maximum and average player's lifetime over N games — N is 50), S (standard deviation of player's lifetime over N games) and $E\{H_n\}$ (stage grid-cell visit average entropy of the opponents over N games) respectively. All three criteria are combined linearly (1)

$$I = \frac{\gamma T + \delta S + \epsilon E\{H_n\}}{\gamma + \delta + \epsilon} \tag{1}$$

where I is the interest value of the predator/prey game; γ, δ and ϵ are criterion weight parameters.

By using a predator/prey game as a test-bed, the interest value computed by (1) proved to be consistent with the judgement of human players [Yannakakis and Hallam, 2005b]. In fact, human player's notion of interestingness seems to highly correlate with the I value. Moreover, given each subject's performance (i.e. score), it is demonstrated that humans agreeing with the interest metric do not judge interest by their performance. Or else, humans disagreeing with the interest metric judge interest by their score or based on other criteria like game control and graphics.

The metric (1) can be applied effectively to any predator/prey computer game because it is based on generic features of this category of games. These features include the time required to kill the prey as well as the predators' entropy throughout the game field. We therefore believe that this metric — or a similar measure of the same concepts — constitutes a generic interest approximation of predator/prey computer games. Evidence demonstrating the interest metric's generality are reported in [Yannakakis and Hallam, 2004b; 2005a] through experiments on dissimilar predator/prey games. Moreover, given the two first interest criteria previously defined, the approach's generality is expandable to all computer games. Indeed, no player likes any computer game that is too hard or too easy to play and, furthermore, any player would enjoy diversity throughout the play of any game. The third interest criterion is applicable to games where spatial diversity is important which, apart from predator/prey games, may also include action, strategy and team sports games according to the computer game genre classification of Laird and van Lent [2000].

4.2 On-Line Learning

The next step we consider in our approach is to enhance the entertainment value of the examined computer game players based on the above-mentioned interest metric. This is

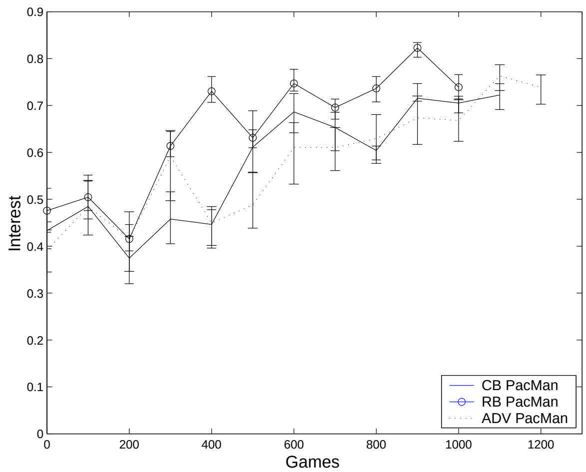

Figure 2: Game interest (average and confidence interval values) over the number of OLL games against different types of Pac-Man player. For reasons of computational effort, the OLL procedure continues for a number of games, large enough to illustrate the mechanism's behavior, after a game of high interest ($I \geq 0.7$) is found.

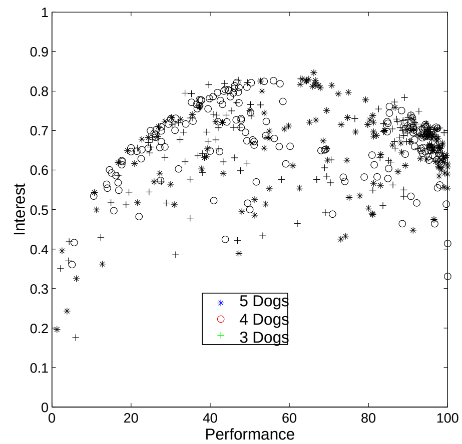

Figure 3: Scatter plot of I and opponent (*Dog*) performance (P) value instances for variants of the Dead End predator/prey game.

achieved collectively through evolutionary learning opponents via on-line interaction. We use an evolutionary machine learning mechanism which is based on the idea of heterogeneous cooperative opponents that learn while they are playing against the player (i.e. on-line). The mechanism is initialized with some well-behaved opponents trained off-line and its purpose is to improve the entertainment perceived by the player. More comprehensively, at each generation of the algorithm:

Step 1: Each opponent is evaluated periodically via an individual reward function, while the game is played.

Step 2: A pure elitism selection method is used where only a small percentage of the fittest solutions is able to breed. The fittest parents clone a number of offspring.

Step 3: Offspring are mutated.

Step 4: The mutated offspring are evaluated briefly in off-line mode, that is, by replacing the least-fit members of the population and playing a short off-line game against a selected computer-programmed opponent. The fitness values of the mutated offspring and the least-fit members are compared and the better ones are kept for the next generation.

The algorithm is terminated when a predetermined number of generations has elapsed or when the I value has reached high values. Successful applications of this algorithm have demonstrated its generality over predator/prey variants [Yannakakis and Hallam, 2004b]; game complexity, game environment topology, playing strategy and initial opponent behavior [Yannakakis and Hallam, 2005a]. Figure 2 illustrates an example of the adaptability and robustness that on-line learning (OLL) demonstrates in a predator/prey game (a modified version of Pac-Man).

For justifiable and realistic character behaviors we follow the animat approach as far as the control of the opponents is concerned. Consequently, we require opponents that demonstrate emergent cooperative behaviors whose inter-communication is based on indirect (implicit) and non-global (partial) information of their game environment.

Figure 3 illustrates a test-bed game application of OLL where the above-mentioned goal is achieved. Given the interest criteria, behaviors of high performance ought to be sacrificed for the sake of highly entertaining games. Consequently, there has to be a compromise between P (performance) and I values. However, as seen in Figure 3, teamwork features within the opponents (*Dogs* in the game of 'Dead End' as introduced in [Park, 2003] and [Yannakakis *et al.*, 2004]) behavior are maintained when interesting games emerge through the on-line learning mechanism. It appears that the most interesting games require a performance ($50 < P < 70$ approximately) which is not achievable without cooperation. Thus, teamwork is present during on-line learning and it furthermore contributes to the emergence of highly interesting games.

5 Player Modeling

The subsequent step to take is to study the players' contribution to their emergence of entertaining games as well as to investigate the relation between the player's type and the generated interest. We do that by investigating Player Modeling (PM) mechanisms' impact on the game's interest when it is combined with on-line adaptive learning procedures. By recording players' actions real-time we dynamically model the player and classify him/her into a player type U (see Figure 1), which will determine features of the AI adaptive process (e.g. on-line learning mechanism).

More specifically, we use Bayesian Networks (BN), trained on computer-guided player data, as a tool for inferring appropriate parameter values for the chosen OLL mechanism. On-line learning is based on the idea of opponents that learn while they are playing against the player which, as previously

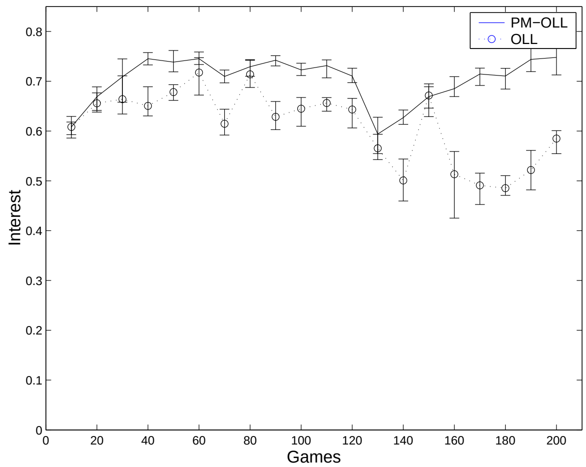

Figure 4: Adaptability test in the Pac-Man game: Random selection of hand-programmed strategies for the player every 10 games.

noted, leads to games of high interest. However, there are a number of parameters and a set of machine learning variants that strongly influence the performance of the on-line learning mechanism. Naive selection of the method and its parameter values may result in disruptive phenomena on the opponents' controllers and lead to unrealistic behavior.

A BN-based mechanism designed to lead to more careful OLL parameter value selection and furthermore to an increasingly interesting game is presented in [Yannakakis and Maragoudakis, 2005]. Results obtained show that PM positively affects the OLL mechanism to generate more entertaining games for the player. In addition, this PM-OLL combination, in comparison to OLL alone, demonstrates faster adaptation to challenging scenarios such as frequent changes of playing strategies (see Figure 4).

6 Player's Emotional Flow

The proposed scheme's part of future work includes the recording of players' behavior real-time by visual means in order to model their dynamical emotional flow E through facial coding procedures. Real-time video data obtained from that environment will be analyzed through automatic face detection and the derived facial expressions will be classified to map basic emotions through algorithms based on the Facial Action Coding System [Eckman, 1979]. This procedure will effectively expose the relation of the player's emotional flow and his/her real-time entertainment which defines one of the objectives of this work. Accordingly, given this relation, the linkage between basic human emotions and features of the on-line adaptive learning will be revealed.

7 AI server and Game test-beds

There is already much evidence for the effectiveness, robustness and adaptability of both OLL and PM mechanisms. However, more complex cooperative games will demonstrate the generality of the methodology over different genres of games. Open source platform, multi-opponent, popularity and on-line gaming potential are the basic game selection criteria, which leave space for FPS and/or real-time strategy (RTS) games.

To cope with the high computational effort, an on-line web server that will host all AI processes (e.g. on-line adaptive learning) needs to be constructed (see Figure 1). The server will monitor game features (e.g. player's actions), reinforce the AI with its real-time generated interest I and adjust the opponent behavior back to the game.

8 Conclusions & Discussion

In this paper we portrayed a scheme for obtaining computer games of richer interactivity and higher entertainment by focusing on the real-time adjustment of the opponent's controller. New unreported results on predator/prey game test-beds demonstrate the effectiveness and fast adaptability of the method in its endeavor to increase the entertainment value of the game and provide further evidence for its successful application to the other genres of game. However, in order for the proposed scheme to be complete, there are still steps that need to be taken towards the automatic recognition of basic emotions of players and their interactivity with the on-line adaptive learning procedures.

The potential of the proposed scheme lies in its innovative endeavor to bring emotional psychology, human-machine interaction and advanced AI techniques to meet upon computer game platforms. As soon as experiments with statistically significant numbers of human subjects are held, this work's outcome will provide important insights to spot the features of computer games — that map to specific emotions — that make them appealing to most humans. Moreover, the playing strategy and emotional features that generate entertainment in games will be exposed contributing important input for the game AI research community.

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