Optimization of Platform Game Levels for Player Experience

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Abstract

We demonstrate an approach to modelling the effects of certain parameters of platform game levels on the players' experience of the game. A version of Super Mario Bros has been adapted for generation of parameterized levels, and experiments are conducted over the web to collect data on the relationship between level design parameters and aspects of player experience. These relationships have been learned using preference learning of neural networks. The acquired models will form the basis for artificial evolution of game levels that elicit desired player emotions.

Introduction

Numerous theories exist regarding what makes computer games fun, as well as which aspects contribute to other types of player experience (Csikszentmihalyi 1990; Koster 2005). Recently, research in player satisfaction modelling has focused on empirically measuring the effects on player experience of changing various aspects of computer games, such as NPC playing styles (Yannakakis and Hallam 2007). Such studies have been conducted using both in-game data collection, questionnaires and physiological measurements (Yannakakis and Hallam 2008a).

A parallel research direction aims to find methods for automatically generating entertaining game content. These efforts see some aspect of a game as variable, defines a fitness ("goodness") function based on a theory of player satisfaction, and uses a learning or optimization algorithm to change the variable aspect of the game so as to become more "fun" according to the definition. The few published papers on this topic deal with optimizing narrative (Nelson, Ashmore, and Mateas 2006), racing tracks (Togelius, De Nardi, and Lucas 2007), platform game levels (Compton and Mateas 2006) and game rules (Togelius and Schmidhuber 2008).

Until now, similar methodologies used for player satisfaction capture and optimization have been concentrating on the impact of NPC behavior (Yannakakis and Hallam 2007) and the adjustment of NPC internal controls for maximizing satisfaction in games (Yannakakis and Hallam 2008b). The work we describe here is concerned with the construction
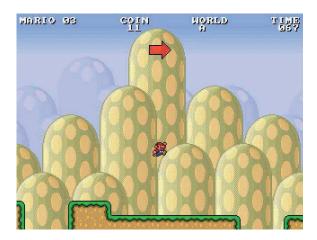

Figure 1: Test-bed game screenshot.

of computational models of player experience derived from gameplay interaction which can be used as fitness functions for game content generation.

Test-bed Platform game

The test-bed platform game used for our studies is a version of *Infinite Mario Bros* (see Figure 1) which is a public domain clone of Nintendo's classic platform game *Super Mario Bros*. The game is playable on the web, where Java source code is also available[1]. While implementing most features of the original game, its standout feature is the automatic generation of levels. Every time a new game is started, levels are randomly generated by traversing a fixed width and adding features (such as blocks, holes and enemies) according to certain heuristics. In our *Infinite Mario Bros* version most of the randomised placement of level features is fixed and deterministic since we concentrate on a few selected game level parameters that affect game experience.

Collecting Player Data

In order to model the relation between variable features of the game and aspects of player experience, these features

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[1]http://www.mojang.com/notch/mario/

first need to be defined, and empirical data needs to be collected. We decided to focus on features which where common to most, if not all, platform games: holes and direction of movement.

Parameterizable level generation

We modified the level generator to create levels according to four controllable parameters presented below. Three of these parameters deal with the number, width and placement of holes. The fourth parameter turns a new function, the direction switch, on or off.

- The number of holes in the level.
- The average width of holes.
- The entropy of holes with respect to which part of the level they appear in (high entropy means uniform distribution, low entropy means that they are mostly in one part of the level).
- Number of direction switches. No direction switch means that the player needs to move from left to right in order to complete the level, as in the original Super Mario Bros. If one or more direction switch is present, the level will suddenly be mirrored at random points, forcing the player to turn around and go the other way, until reaching the end of the level or the next direction switch.

Two states (low and high) for each of the four controllable parameters above are investigated. This results in $2^4 = 16$ different variants of the game.

Experimental methodology

We designed a game survey study to solicit pairwise emotional preferences of subjects playing different variants of the test-bed game by following the experimental protocol proposed in (Yannakakis and Hallam 2008a). Each subject plays a predefined set of four games in pairs. For each of the two pairs of games A and B, subjects report their preference for several emotional states (e.g. fun) using a 4-alternative forced choice (4-AFC) protocol.

Several statistical features are extracted from playing data which are logged during gameplay and include game completion time, time spent on various tasks (e.g. jumping, running), information on collected items (e.g. type and amount), killed enemies (e.g. type, amount, way of killing) and information on how the player died.

Data is collected over the Internet. Users are recruited via posts on blogs and mailing lists and directed to a web page containing an applet implementing the game and questionnaire [2]. We have so far collected enough data to have at least 2 preference instances for each pair of game variants ($C_2^{16} = 120$ participants), but data collection is still in progress and new data will be used to improve our models.

Modelling and optimizing player experience

We assumed there is an unknown function between individual playing characteristics (e.g. number of coins gathered),

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[2]The game and questionnaire, which will be demonstrated at the conference, is available at www.bluenight.dk/mario.php

controllable game level features (e.g. number of holes) and reported emotional preferences, and proceeded to try to predict the latter from the former.

Using neuroevolutionary preference learning of simple nonlinear perceptrons (Yannakakis and Hallam 2008a), we have been able to accurately predict certain player emotions from gameplay features. For example, whether the player is frustrated by the current game can be predicted with an accuracy of 88.66 looking at just four behavioral features. Predicting player emotions based only on controllable features is harder, but good accuracy can be achieved using nonlinear models such as multilayer perceptrons.

Work is currently in progress to use evolutionary algorithms to optimize the level design parameters (relating to holes and switches) for different objectives. We aim to be able to generate levels that tailor the playing experience according to the needs of the game design (e.g. a challenging level combined with a frustrating experience). The success of our optimization attempts will be validated with further user studies.

References

Compton, K., and Mateas, M. 2006. Procedural level design for platform games. In *Proceedings of the Artificial Intelligence and Interactive Digital Entertainment International Conference (AIIDE)*.

Csikszentmihalyi, M. 1990. *Flow: the Psychology of Optimal Experience*. Harper Collins.

Koster, R. 2005. *A theory of fun for game design*. Paraglyph press.

Nelson, M. J.; Ashmore, C.; and Mateas, M. 2006. Authoring an interactive narrative with declarative optimization-based drama management. In *Proceedings of the Artificial Intelligence and Interactive Digital Entertainment International Conference (AIIDE)*.

Togelius, J., and Schmidhuber, J. 2008. An experiment in automatic game design. In *Proceedings of the IEEE Symposium on Computational Intelligence and Games*.

Togelius, J.; De Nardi, R.; and Lucas, S. M. 2007. Towards automatic personalised content creation in racing games. In *Proceedings of the IEEE Symposium on Computational Intelligence and Games*.

Yannakakis, G. N., and Hallam, J. 2007. Towards optimizing entertainment in computer games. *Applied Artificial Intelligence* 21:933–971.

Yannakakis, G. N., and Hallam, J. 2008a. Entertainment modeling through physiology in physical play. *International Journal of Human-Computer Studies* 66:741–755.

Yannakakis, G. N., and Hallam, J. 2008b. Real-time Adaptation of Augmented-Reality Games for Optimizing Player Satisfaction. In *Proceedings of the IEEE Symposium on Computational Intelligence and Games*, 103–110. Perth, Australia: IEEE.