A Quantitative Approach for Modeling and Personalizing Player Experience in First-Person Shooter Games

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Abstract. In this paper, we describe a methodology for capturing player experience while interacting with a game and we present a data-driven approach for modeling this interaction. We believe the best way to adapt games to a specific player is to use quantitative models of player experience derived from the in-game interaction. Therefore, we rely on crowd-sourced data collected about game context, players behavior and players self-reports of different affective states. Based on this information, we construct estimators of player experience using neuroevolutionary preference learning. We present the experimental setup and the results obtained from a recent case study where accurate estimators were constructed based on information collected from players playing a first-person shooter game. The framework presented is part of a bigger picture where the generated models are utilized to tailor content generation to particular player's needs and playing characteristics.

Keywords: Player Experience Modeling, Affect Recognition, Procedural Content Generation, Adaptive Games

1 Introduction

Understanding players' interaction with a game has been the focus of many research studies. Several theoretical attempts have been proposed that aim at identifying patterns of player behaviors and building qualitative theories that relates aspects of game design to key concepts of gameplay experiences [9, 8, 2, 3]. While these theories constitute much of our understanding of the in-game interaction, they lack the necessary details to be implemented in computational models. Moreover, most of these theories are based on general high-level observations which makes them unsuitable for the personalization of content. Having an algorithm that, given information about the player style, can predict the appeal of the game content to this specific player is useful for many reasons: first, this would help us better understand the game-player relationship; second, such an algorithm could allow us to identify the aspects of the game content that contribute to player entertainment and finally, this would allow us to achieve the ultimate aim of most of the studies in the field of affective computing, that is being able to adapt the game to the player and thus successfully closing the affective loop in games [14, 6, 10, 1].

An interesting direction that has received increasing attention is Procedural Content Generation (PCG) in which artificial and computational intelligence methods have been utilized to generate different aspects of content with or without human interference [15]. An interesting direction within the automatic content generation is the creation of personalized content [7, 5, 13]. The first step towards achieving such goal is to model the relationship between user experience and content. This can be done by the construction of data-driven models based on data collected from the interaction between the user and the digital content and annotating this data with user experience tags [17]. The *Experience-Driven Procedural Content Generation* (ED-PCG) framework [17] suggests the different components that should be implemented to realize this goal.

In this paper, we advocate the use of an ED-PCG approach to adapt games to players, and present an experiment conducted within this direction. We follow a similar protocol to the one followed in our previous attempts to capture and personalize player experience in a clone of the popular game *Super Mario Bros* [11]. We extend our previous attempts through investigating a whole new game genre, more specifically, we follow similar methodology to model player experience in a First-Person Shooter (FPS) game. This allows us to test the generality of the suggested modeling framework and check how well it scales when applied in a more complex environment and more sophisticated, richer, form of the in-game interaction.

Within this context, the presented work employs a fusion scheme of game-content parameters and game-performance indicators in order to predict player preferences between different game variants. Players' preferences are identified via comparative questionnaires and different game variants are ranked with respect to frustration, engagement and challenge. Automatic feature selection and neuroevolutionary preference learning are employed to select a subset of appropriate features that yield accurate predictors of the reported affects. Results show that accurate player experience models (accuracy higher that 71%) can be constructed.

2 The Testbed Game: Sauerbraten

We used a modified version of the FPS game called *Sauerbraten* as a testbed for our experiment (see Figure 1 for a screenshot of the game). The game is built on a game engine called *Cube*, and both game and game engine are public domain and freely available online[3]. The game can be played in a single player or multiplayer mode. For the experiments presented in this paper, we focus only on the single player mode to eliminate the other effects. The levels employed are

[3] http://cubeengine.com

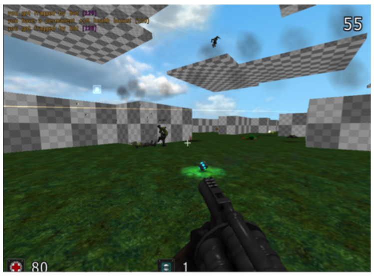

Fig. 1. A screen shot from the FPS game used as a testbed.

composed of two-layered with Non-Player Characters (NPCs) spawned along the levels. Each game session lasts for two minutes and the goal of the game is for the player to get the highest score possible by killing as many of the enemies as possible.

The player can kill enemies by shooting at them using different types of weapons that differ in their accuracy, damage caused and shooting range. NPCs can also shot at the player causing health lose and eventually death. The amount of health lose depends on the type of the weapon used for shooting. Every time the player is killed, he/she looses one point and he/she is re-spawned again as long as he/she still has time left to play.

3 Player Experience Modeling Framework

The Player Experience Modeling (PEM) framework followed consists of two main steps: crowed-sourcing data from players, and constructing data-driven models of player experience. The ultimate aim of the framework is to construct models that approximate the relationship between features of game content and player behavior and reported affective states.

3.1 Data Collection

Game surveys were conducted to collect information about players' interaction with the games and their affective states. The protocol suggested in [18] was followed to design and solicit the information. According to the protocol, players are presented with a pair of two sessions that differ along one or more aspects of game content. While playing, detailed information about player behavior and actions were recorded. After playing each pair, players were asked to report their emotional/behavioral states following the four-alternative forced choice protocol that asks the players to express their preference of the three states: *engagement*, *frustration* and *challenge*. The selection of these states is based on earlier game survey studies [11, 4] and our intention to capture both affective and cognitive/behavioral components of gameplay experience. Moreover, we want to keep the self-reporting as minimal as possible so that experience disruption is minimized. Pairwise preferences have been adopted for this study because of their numerous advantages over rating-based questionnaires [16]. The questionnaires presented are of the form: "Which game was more E?" where E is the state under investigation. The possible answers are: (1) game A [B] was more E than game B [A] (2) both equally or (3) neither.

A total number of 115 players participated in the data collection experiment and several features were extracted from the recorded data and used to build models of player experience. The participants were all first to fifth-year students at the Faculty of Information Technology Engineering at the University of Damascus.

3.2 Feature Extraction

Several features about the content of the game presented to the players as well as gameplay features capturing different aspects of player behavior and the in-game interaction were extracted from the game sessions recorded. The game engine was modified to allow recording the gameplay features while the game is being played. A complete log is also saved permitting the extraction of additional features after data collection. Table 1 presents a subset of the features extracted. The context features presented are the ones used to construct the variations of the game content presented to the players.

Table 1. Gameplay and expressivity features extracted from the data recorded.

Category	Feature	Description
		GamePlay Features
Time	t_{life}	Duration of play
	t_{weapon}	Time spent using weapons (%)
	t_{shoot}	Time spent shooting (%)
	t_{still}	Time spent not moving (%)
	t_{jump}	Time spent jumping (%)
Interaction with items	n_{health}	Health items collected (%)
	n_{armour}	Armours collected (%)
Interaction with enemies	e_{kill}	Number of times the player kills an enemy (%)
	p_{hit}	Number of times the player receives a hit from an enemy (%)
	e_{hit}	Number of times the player hits an enemy (%)
Miscellaneous	n_{death}	Number of times the player died
	s_{acc}	Shooting accuracy
		Context Features
	E	Number of enemies
	E_{skill}	Skill level of enemies
	W_{type}	Type of weapons including explosive and non-explosive weapons
	H	Number of health items
	R	Number of resources such as bullets and armors

4 Preference Learning for Modeling Playing Experience

The data collected in the previous step is used to construct accurate estimators of player experience. Models of player experience were built using neuroevolutionary preference learning [18]. The features extracted in the previous step are set as input to a feature selection method to chose a subset of relevant features for predicting each emotional state using forward feature selection method. The selected subset of features are then used to build the neural network models which are trained to adjust the weight so that their output matches the reported preferences. The topologies of the models were also optimized for best prediction accuracies.

Different subsets of features were selected to predict each emotional state pointing out to various roles each feature plays to elicit the different affective states. Some of the features, such as the number of enemies and the their skill, were selected as predictors of engagement and challenge suggesting an implicit relationship between these two states. Accurate estimators of player experience were constructed with average accuracies of 71.26%, 81.42% and 97.27% for engagement, frustration and challenge, respectively. Table 2 presents information about the features selected and the average prediction accuracies obtained over five runs. The results indicate that challenge is the easier to predict while engagement is the hardest with the largest subset of features and the lowest accuracy.

Table 2. Features selected from the set of extracted parameters for predicting engagement, frustration and challenge. The table also presents the corresponding average ($Performance$) values obtained. Context features also appear in bold.

	Engagement	Frustration	Challenge
$Selected features$	p_{hit}	p_{hit}	t_{life}
	t_{still}	e_{hit}	n_{death}
	$\mathbf{E_{skill}}$	e_{kill}	$\mathbf{E}$
	$\mathbf{E}$	t_{still}	$\mathbf{E_{skill}}$
	$\mathbf{W_{type}}$		$\mathbf{W_{type}}$
	t_{exp}		t_{weapon}
	n_{armour}		
$Performance$	71.26%	81.42%	97.27%

It is worth noticing that none of the content features were selected for predicting frustration which indicates the this emotional state is more directly influenced by player behavior unlike engagement and challenge where three out of the four context features were selected highlighting the impact of context information on these two states.

5 Personalizing Player Experience

The models derived can be used to personalize the game context tailoring the content generation to desired levels of engagement, frustration or challenge for an individual player based on his/her playing style. This can be achieved by first adjusting the model for control —by including the set of context parameters into the input of the models— and then searching the content space for game content that, taken together with player specific gameplay characteristics, can optimize a specific experience. This new player dependent content is then presented to the player closing the affective loop in games.

Depending on the size of the content space, exhaustive search or global stochastic search methods can be employed. This approach has been tested to personalize player experience in our previous work on a platform game [12] with encouraging results and we are in an ongoing effort to investigate the applicability of the method for the FPS game under investigation. The preliminary results show that the models are able to recognize different playing characteristics and generate personalized content accordingly. However, more experiments and evaluation are required if we are to draw robust conclusions.

6 Conclusions and future work

In this paper we presented a scheme for modeling player experience from behavior and context features. Players' reports of three emotional states (engagement, frustration and challenge) were collected along with features from game sessions. Feature extraction, selection and neuroevolutionary preference learning methods were employed to approximate the function between context and behavior features, and reported affective states of players. Different subsets of features were selected to predict each emotional state and accurate estimators were constructed.

A game personalization approach is also presented in which the constructed models can be used to evaluate the content and chose the best fit for each individual needs. The experiments and results presented in this paper are part of an ongoing project that aims at validating the extendibility of the player experience modeling framework by applying it on different game genres and for the purpose of closing the affective loop in games. More experiments are currently undertaken to generate and evaluate the models and the personalized content. Moreover, we are investigating the use of other, more expressive, modeling techniques that could potentially be used to help us better understand the in-game interaction and the effect of context on player behavior. Alternative personalization approaches could also be investigated.

The framework followed was previously tested for a platform game and the current paper show its applicability to FPS games. We believe that the same methodology can scale to other games from the same genre or other game genres and that the models constructed can be generalized to capture player experience in other games.

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