Towards Player-Driven Procedural Content Generation

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ABSTRACT

Generating immersive game content is one of the ultimate goals for a game designer. This goal can be achieved by realizing the fact that players' perception of the same game differ according to a number of factors including: players' personality, playing styles, expertise and culture background. While one player might find the game immersive, others may quit playing as a result of encountering a seemingly insoluble problem. One promising avenue towards optimizing the gameplay experience for individual game players is to tailor player experience in real-time via automatic game content generation. Specifying the aspects of the game that have the major influence on the gameplay experience, identifying the relationship between these aspect and each individual experience and defining a mechanism for tailoring the game content according to each individual needs are important steps towards player-driven content generation.

Keywords

Player modeling, procedural content generation, game personalization, game adaptation, neuroevolutionary preference learning

1. INTRODUCTION

As players tend to vary significantly in their preferences, it would be useful to have an algorithm that could observe a human playing a game and accurately judge what the human is experiencing as he/she is playing, as this could allow us to adapt the game to the player, and also help us understand how human affect is expressed in behavior. Our approach towards achieving this goal is first to construct accurate models of the relationship between player experience and game content. This requires the construction of data-driven models based on data collected about the game, the player behavior and correlating this data with data annotated with player experience tags. Our ultimate aim is to tailor player experience in real-time via automatic game content generation based on accurate computational models of in-game player experience.

2. RELATED WORK

The following sections review previous work on topics related to our work.

2.1 Modeling of Player's Emotion

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Emotions are critical in game design. Identifying what is "fun" and what makes computer games more engaging have been the focus of many research [3, 7]. Closing the *affective loop* [6] is one of the ultimate aims of the research carried out in the field of affective computing [10]. A few attempts can be found on incorporating players' emotions into the game in a closed-loop manner where player's emotion is actively manipulated to ensure engagement [4]. Existing work [22, 2] demonstrates the power of using affective player models to generate in-game situations of high interest and satisfaction for the players. Most studies in this direction can be classified as qualitative in a sense that they have been based on intuition in combination with some qualitative theories of player experience [3, 7]. On the other hand, the quantitative approaches have received more attention recently. Computational intelligence techniques have been adopted recently to build quantitative models of player experience for platform games [9, 23].

2.2 Experience-Driven Procedural Content Generation

A Research direction that has received increased attention recently is the automatic generation of game content. Procedural Content Generation (PCG) via artificial and computational intelligence methods have been utilized to generate different aspects of content with or without human interference. A recent overview of recently used techniques can be found in [19, 24]. An interesting direction within the automatic content generation is the creation of personalized content [5, 18, 12]. Optimization of game aspects based on empirically derived models has mostly been focused on the impact of non player character NPC behavior and the adjustment of NPC behavioral parameters for maximizing satisfaction in games [1, 8]. Few attempts emerged recently focusing on adapting game content using computational models of player emotion built from the interaction between the player and the game [20, 9]. The literature on personalized and player-adaptive PCG is so far scarce, as it is a new research direction.

3. PLAYER-DRIVEN PROCEDURAL CONTENT GENERATION

Mainly motivated by the current lack of a quantitative entertainment formulation of computer games, the need for a better understanding of the relationship between game content and players' affective state and the increasing interest in personalized and online (during play) automatic adaptation mechanisms, the focus of the work carried out is on constructing an estimator of players' emotional state derived from the in-game interaction, this can serve as a fitness function for game content generation, the content generation will be done online, serving players new game content based on how they individually have played previously. To achieve these goals a number of fundamental objectives need to be carried out:

1. Constructing an accurate indicator of player experience based on the interaction between the player and the game.

2. Applying an online adaptation to change game content to accommodate specific player experience.

In the work carried out we are trying to give answers to the following sub-goals that the aforementioned research objectives generate:

1. How can we recognize players' affect while playing?

2. What are the features from the game content and players' in-game behavior that help predict players' affect?

3. How to construct models of players' experience that can predict players' emotional state with high accuracy?

4. What is the best representation of players' behavior and game content that can be used to construct the models?

5. How and how often the game should be adapted to enrich particular player experience?

We chose *Super Mario Bros* as the testbed for our research. The remaining sections present our approach to tackle the research questions and explore our view on the future directions.

3.1 Data Collection

In our study we rely on data expressed by players themselves about their playing experience along with features of how they play the game and we construct our models based on these data. The following features have been extracted from data collected from hundreds of players playing Infinite Mario Bros.

- Content features: these are also named *Controllable* as they are used to generate the levels and are varied to make sure several variants of the game are played and compared. These features have been selected with the intent to cover the features that have the most impact on the investigated affective states [14, 15].

- Gameplay Features: All player actions and interactions with game items and their corresponding time-stamps have been recorded with the full trajectory of Mario.

- Reported Player Experience: Player experience is annotated via a 4-alternative forced choice questionnaire. The questionnaire asks the player to report the preferred game for the three user states: engagement, challenge and frustration. The selection of these states is based on earlier game survey studies [9] and our intention to capture both affective and cognitive/behavioral components of gameplay experience [24].

A number of limitations are embedded in the players' self-reporting experience modeling [24]. To overcome these limitations, a set of experiments has been conducted to assess the estimation of players' affect by introducing *expressivity features*; a set of head movement parameters extracted for creating behavioral correlations to game events by analyzing video recording of players.

3.2 Feature Representation

Two types of representations have been used for the recorded content and gameplay features via direct and sequential feature extraction. Direct features provide quantitative measure about game content and playing style such as the number of collected items. Alternatively, sequential features allow including features that are based on ordering in space or time and yields patterns that might be directly linked to player experience. Sequential features have been extracted by applying sequence mining techniques [25, 16] to extract useful patterns from the sequences generated [15, 13].

3.3 Player Experience Modeling

The very first step towards designing accurate, reliable and computationally efficient models of players' experience is to identify relevant features from game content and gameplay that affect player experience. A large set of features have been extracted and not all of these features are necessarily relevant for modeling player experience. Therefore, automatic features selection is used to extract the minimal subset of relevant features for predicting players' affective states with high accuracy. Neuroevolutionary preference learning [21] has been used in order to construct models that approximate the function between the selected subset of gameplay features, controllable features, expressivity features and reported affective preferences. Different experiments with different setups and features has been conducted on different portions of the dataset [14, 15, 13, 11]. Using the proposed approach, we were able to predict engagement with accuracy up to 75.21%. The best constructed model for predicting frustration has an accuracy of 85.88%, while challenge can be best predicted with an accuracy of 91.23% [13].

3.4 Online Game Adaptation

Once a model that capture player experience has been constructed, and as an initiative to close the affective-loop, the content generator needs to search within the resulting search space for content that maximizes particular aspects of player experience. Ideally, the content generator should be able to identify if, how much and how often content should be generated for a particular player [24].

3.4.1 Adaptation Frequency

Successfully defining the smallest possible segment of the level for which the player experience models can still predict reported affect with acceptable accuracy is important since this segment size can then potentially be used to set the frequency of a real-time adaptation mechanism for the purpose of maximizing specific players' affective state. Therefore, the game sessions have been segmented into up to three segments and models have been constructed from the different segments. The results suggested that player reported challenge can be best predicted with longer sessions' size than the ones needed for predicting frustration or engagement [13].

3.4.2 Adapting Game Content

A step toward achieving the online content adaptation was carried out in [14] where the constructed models of players' experience from content and gameplay direct features were used to optimize game levels for particular players. Since content was represented via a small number of dimensions (four controllable features were used in that experiment), exhaustive search was used as the online adaptation mechanism. The space of controllable features has been explored to find the best combination of game features that yields the best performance in predicting the player's reported emotional states. This best combination found was then used to set the value for the four controllable features to generate a new level that is personalized according to the behavior of a specific player [14].

4. CONCLUSION AND FUTURE WORK

The work carried out is primarily based on two research questions: how to accurately model player experience and how to tailor game content generation according to specific player behavior. Super Mario Bros game was used as the testbed. A number of experiments have been conducted to construct player experience models based of different categories of features collected from hundreds of players. Direct and sequential feature representation have been employed and tested for constructing efficient models. The experiments showed that players' reported affect of the three emotional states, engagement, frustration and challenge could be predicted with high accuracies using automatic feature selection and neuroevolutionary preference learning. As for game adaptation, our goal is to give answers to the questions of how, how much and how often game content should be adapted for a particular player. To answer these questions, the smallest possible sessions' size for which the constructed models can still predict the reported affect with high accuracies has been investigated. This size can be potentially used to set the adaptation frequency. A further experiment has been conducted to generate personalized level by exhaustively searching the content space for a combination that maximizes specific player experience. The future directions include constructing a more accurate models based on more controllable features. Grammatical evolution is being adopted to construct playable levels and a study will be conducted to analyze and construct player experience models from these levels. Another direction includes a more in-depth investigation of the adaptation mechanism. Evolutionary algorithms could be used to explore the content space when exhaustive search algorithm could fail due to larger search space. Other approaches could also be investigated to personalize the structure of the player models. For this purpose, the NeuroEvolution Augmenting Topologies (NEAT) [17] could be potentially used. A thorough analysis of the direct and sequential features selected by automatic feature selection is an interesting direction towards constructing data-driven models of game aesthetics that can also be used by designers to construct more engaging, challenging, or frustrating content. The work presented and the approach followed constitute an important step for future work on other game genre. The findings can also be generalized and applied for personalizing other digital media content based on human-computer interactions.

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