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AI for Game Spectators: Rise of PPG

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Abstract

This position paper describes an AI application for game spectators, e.g., those watching Twitch. The aim of this application is to automatically generate game plays by non-player characters -- not human players -- and recommend those plays to spectators. The generation part leads to development of a new field: procedural play generation (PPG). The recommendation part requires new techniques in recommender systems (RS) for incorporation of play content into RS to obtain promising recommendation results. Rather than proposing solutions to all relevant topics, this paper aims at drawing attention to this new field and serves as a seed for discussion and collaboration among the readers, workshop participants, and authors.

Why Spectators?

Nowadays, more than a million spectators watch game streaming platforms such as Twitch each month. This kind of phenomenon makes games as promising media and has resulted in a number of research studies focusing on spectators (Cheung and Huang 2011; Smith et al. 2013; Jia et al. 2016). According to Smith et al., there are three major spectator communities in Twitch: “Speedrunning”, “E-sports” and “Let’s Play” that are composed of plays by players whose aim is to complete a game as fast as possible, plays from professional matches by competitive players, and plays by players who play and stream their games to entertain themselves or others, respectively.

As for spectator types, E-sports spectators were identified by Cheung and Huang to have nine types or personas, such as those who simply find watching games entertaining (Entertained) or those who want to gain game knowledge or new skills through watching games (Curious or Pupil). Smith et al. adopted these nine types in their analysis on the Let’s Play community. In our work, as with them, we focus on the Let’s Play community because it accommodates more variety of game experiences. In addition, we aim at automatic generation of entertaining game plays by non-player characters (AIs) and recommending such plays to spectators, especially those of the Entertained persona.

Play Personas, Procedural Personas, and Play Arcs

Play personas representing archetypical game players were first studied by Canossa and Drachen (2009). Based on this play-persona framework, Holmgård et al. (2014) proposed the concept of procedural personas that individually model players of a given play persona and allow game designers to understand in advance how their games will be actually played. However, procedural personas, focusing on play styles, cannot codify the story arc of a game play.

Vonnegut (1981) proposed that the shape of a story can be readily defined by the transition of the protagonist’s fortune. Vonnegut’s concept was applied by Reagan et al. (2016) to analyze 1,327 stories from Project Gutenberg’s fiction collection, from which six basic shapes were found. We argue that besides play styles, story arcs play an important role in generation of entertaining game plays.

For games, story arcs were referred to as play arcs by Costikyan (2013). We refine the definition of a play arc as a time-series of significant in-game events that construct the narrative in a game play. For example, in a fighting game, a player arc, in its simplest form, can be derived using the remaining HP of the player character divided by that of the opponent. According to our experience, as in stories (Reagan et al. 2016), basic but dramatic play arcs for fighting games include “Cinderella” (rise-fall-rise) and “Oedipus” (fall-rise-fall), representing a thrilling winning situation and losing one by the player character, respectively.

Procedural Play Generation and Recommendation Systems

Here, we coin procedural play generation (PPG) to contrast with procedural content generation (PCG). Namely, PPG

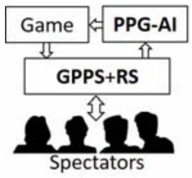

Figure 1: Conceptual diagram of AI for game spectators

focuses on automatic generation of game plays while PCG on other kind of content such as maps, levels, or game rules (Shaker et al. 2016). A Let's Play video usually consists of the footage of a game play and that of the player while playing the game plus live commentary. At the current stage, we limit our work to automatic generation of game-play footages.

Our conceptual diagram of AI for game spectators is shown in Fig. 1. In this figure, PPG-AI stands for AIs whose role is to play the game so that a resulting game play could meet spectators' play-persona preference and play-arc preference. Candidates for such AIs include those developed in general video game playing (GVGP), e.g., an AI using a combination of Monte-Carlo tree search (MCTS) and reinforcement learning (Chu et al. 2016). However, unlike AIs for GVGP that focus on maximizing their performance in an unseen game, PPG-AIs must meet the aforementioned preferences, leading to a challenge in formulation of the MCTS evaluation function. A possible solution for this is to evolve the function so as to obtain a high predicted rating by the spectator for a generated gameplay, by using evolutionary computation techniques such as genetic programming (Benbassat and Sipper 2013).

Thereby, another challenging issue for PPG is that of predicting a rating for every generated game play. For this task, such a rating can be estimated using the actual ratings by the same spectator for similar game plays stored in a game-play portal site (GPPS), equipped with a recommender system (GPPS+RS in Fig. 1). Similar game plays are those in the same neighborhood in play feature space, which is constructed by features extracted using state-of-the-art feature-extraction techniques used in, e.g., video classification with deep networks (Ng et al. 2015). Once a generated game play has been determined to have a high rating, it is then added to the GPPS+RS for being displayed or recommended to and rated by spectators. As for RS, a promising approach that should be further explored is machine learning (Kim and Kim 2014).

Conclusions and Future work

We discussed a promising and challenging application in regard to what's next for AI in games: AI for game spectators, leading to the rise of PPG. We also pointed out a number of candidate techniques for implementing PPG and RS. At the workshop, preliminary results using two game platforms: FightingICE and Science Birds (Angry Birds clone) will be shown. The former is developed by us and has been used in the Fighting Game AI Competition at CIG since 2014 while the latter game was used in the 2016 Angry Birds AI Level Generation Competition. In future, we plan to extend our work to other games such as StarCraft, used in game AI competitions at both CIG and AIIDE. Automatic generation of entertaining player footages and live commentary are challenging and also left as our future work.

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