Keeping the Player on an Emotional Trajectory in Interactive Storytelling

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Abstract

Artificial Intelligence (AI) techniques have been widely used in video games to control non-playable characters. More recently, AI has been applied to automated story generation with the objective of managing the player's experience in an interactive narrative. Such AI experience managers can generate and adapt narrative dynamically, often in response to the player's in-game actions. We implement and evaluate a recently proposed AI experience manager, PACE, which predicts the player's emotional response to a narrative event and uses such predictions to shape the narrative to keep the player on an author-supplied target emotional curve.

1 Introduction

Storytelling is not only a way to pass or even represent knowledge (Szilas 2015) but also a means of eliciting emotions from the audience. A recent study on story evolution over serial reproduction suggests that people maintain affective dimensions (e.g., surprise) while modifying events in a story (Breithaupt, Brower, and Whaley 2015). Video games add a new dimension to storytelling by allowing the audience to change the narrative through their actions. Such player agency has the potential to create personalized stories that the audience can connect with. Exploitation of this potential has been explored by numerous games, among them Bioware's *Mass Effect* (Bioware 2010) and *Dragon Age* (Bioware 2009) series with critical acclaim (VanOrd 2014; Makuch 2014).

Enabling the audience (i.e., the player) to change the narrative with their in-game actions gives rise to a multitude of possible stories and makes it difficult for the author to ensure that each of them will elicit an intended emotional response from the audience. One solution is to modify the narrative dynamically not only in direct response to the player's actions but also in order to achieve authorial objectives. This problem of on-the-fly experience management has been tackled with AI managers (Riedl and Bulitko 2012). For instance, the *Automated Story Director* (Riedl et al. 2008) modified the story of the little red riding hood (Grimm and Grimm 1857) delivering goods to her grandmother in response to the player's actions (e.g., killing the wolf in the forest) so that the authorial goals (e.g., the grandmother needs to be eaten) are still accomplished. To do this, the AI manager used a formal encoding of the domain of the narrative discourse and ran automated planners to generate continuations of the narrative to accomplish authorial goals.

Frequently, multiple automatically planned narrative continuations can achieve authorial goals. For instance, if Red controlled by the player kills the wolf early in the game, the authorial goal of eating her grandmother can be achieved by either introducing another wolf or resurrecting the deceased wolf via a magic fairy. Which plan would elicit the desirable emotional response from the player? Poo Hernandez, Bulitko, and St.Hilaire (2014) answer this question by computationally predicting the player's emotional reactions to automatically planned narratives and then choosing the narrative predicted to elicit the reaction closest to that specified by the author. The advantage of this approach is that the author of such an interactive narrative does not even need to specify concrete narrative events/goals (as was required by previous managers (Riedl et al. 2008; Ramirez Sanabria and Bulitko 2014)). Instead, he/she can specify the desired emotion to be elicited from the player at various stages of the story. In effect, the author specifies a target *emotional trajectory* at the story development time. The AI manager then attempts to keep any player on it during the game playthrough by selecting the next bit of narrative from the candidates generated by an AI planner. This approach was recently published under the name of *PACE: Player Appraisal Controlling Emotions* (Poo Hernandez, Bulitko, and St.Hilaire 2014).

Our paper makes two contributions. We present the first implementation of PACE by adding it to a novel narrative-based video game called *iGiselle*. Second, we evaluate the effectiveness of PACE via a formal user study. Although we find that PACE may be capable of increasing the player's feeling of fun for people who do not identify themselves as gamers, the results are inconclusive.

The rest of the paper is organized as follows. In Section 2 we formulate the problem. Section 3 reviews related work. We recap the operation of PACE in Section 4 and present its implementation in a video game in Section 5. In Section 6 we present the results of PACE evaluation. We then conclude the paper with future work directions.

2 Problem Formulation

The problem we consider in this paper is to build an AI experience manager that will manage narrative experience of a player in a video game in a way intended by the author. We adopt three common performance measures used to evaluate an AI experience manager in a user study. Specifically, we will measure the player's self-reported feeling of *fun*, *agency* and *plot/character believability* during their playthrough. We also adopt Poo Hernandez, Bulitko, and St.Hilaire's hypothesis that the player's sense of fun, agency and believability can be manipulated by guiding him or her through a series of emotional states. Specifically, when selecting the next narrative segment to be presented to the player, the AI experience manager should select the one that it predicts to elicit emotions in the player closest to the emotions the author intended at this stage of the story. Therefore, in our problem formulation, an AI experience manager takes a target emotional trajectory for the narrative as an input and outputs a sequence of narrative segments consistent with the player's in-game actions as well as attempting to keep the player on the emotional trajectory.

3 Related Work

Existing work relevant to the problem introduced in the previous section comes from several fields of research. The first field is AI experience management in the context of interactive narrative in video-game-like systems. The *Automated Story Director* (ASD) (Riedl et al. 2008) represents the narrative as a plan and uses an AI planner *Longbow* (Young 1994) to automatically generate a narrative from a formal description of the story world and *a priori* given authorial goals. Should several plans be generated, the one closest to an author-provided exemplar narrative is selected. The ASD does not allow the author to explicitly specify target emotions elicited in the player. However, the automated planning approach of the ASD is used within PACE, the AI manager we implement and evaluate in this paper.

Player-specific Automated Storytelling (PAST) (Ramirez Sanabria and Bulitko 2014) combines the AI planner of the ASD and the playstyle model of *Player Specific Stories via Automatically Generated Events* (PaSSAGE) (Thue et al. 2007; 2011) in an attempt to modify the narrative in a player-specific way. *Longbow* within PAST generates a plan based on its proximity to an author-provided exemplar narrative combined with the alignment of the plan to the player model. The model was based on the RPG playstyle inclinations of Laws (2002) and was acquired in game time by observing the player. There was neither explicit predictions of player's emotional response to various narratives nor a mechanism for the author to specify different emotional targets at different story stages.

The other field of existing work focuses on inferring the player's emotional state (Lin, Spraragen, and Zyda 2012). Appraisal-style models computationally predict the player's emotional state as a result of an interaction between the player's goals and the likelihood that such goals will be achieved given a candidate narrative. To illustrate, the possibility of achieving a goal elicits the emotion of hope while the certainty of success elicits joy. A well-known appraisal model is OCC (Ortony, Clore, and Collins 1990). OCC is capable of modeling 22 different emotions and has been used in several systems such as *EM* (Reilly 1996), *Émile* (Gratch 2000) and *FearNot!* (Aylett et al. 2005; 2007). *Émile* computes the probability of an agent's success based on its current goals and the plan the agent has developed to achieve them and uses this probability to determine the agent's emotional state. *EMotion and Adaptation* (EMA) (Marsella and Gratch 2003) compliments an appraisal-based emotion modeling with a coping mechanism and thus can be used to control an agent's appearance (Kenny et al. 2007) as well as its actions within a game. PACE, the AI Manager we implement and evaluate in this paper, incorporates an appraisal-style model to predict the player's emotional response to candidate narratives.

Several AI experience managers have represented the player's emotions and used them to shape the narrative. *Moe* (Weyhrauch and Bates 1997) was one of the first experience managers to use a target intensity curve and annotations on narrative events supplied by the author to guide the narrative. A similar approach is implemented in *Façade* (Mateas and Stern 2003) where each plot point is manually annotated with a value representing the tension it introduces to the story. Then *Façade*'s experience manager chooses the plot point whose tension would be closest to the target tension curve provided by the author. A similar approach is also used in *Distributed Drama Management* (DDM) (Weallans, Louchart, and Aylett 2012) where the non-playable characters model the player's current and future emotions and use them to choose an action to perform. *Moe* and *Façade* do not use an explicit player modeling, and it is assumed that all players react in the same way to a narrative event. PACE's approach is similar but allows the author to specify a wider range of emotions and recognizes that a narrative event can elicit different emotional responses from different players. DDM does model the player's emotions through the interaction with NPCs, however because it is NPC-centric, if the NPC's goals and actions are contrary to what the story requires to elicit a certain emotion from the player, DDM will not be able to implement it. PACE avoids this predicament by giving the experience manager control over the entire narrative including all NPCs.

Advances in biometric readers have allowed researchers to attempt to explicitly read the player's emotional state and use it to shape the game. Skin conductance, heart rate and facial electromyography are used to infer the player's level of tension and modify the level layout and enemy encounters (Nogueira et al. 2013). However, biometric-driven approaches can directly assess only player's current state whereas planning a forthcoming narrative event requires a prediction of the player's emotional response to it. By using an appraisal model of emotions, PACE attempts to predict the player's emotional response to a future narrative event.

4 Player Appraisal Controlling Emotions

In this paper we implement and evaluate PACE, an AI experience manager (Poo Hernandez, Bulitko, and St.Hilaire 2014). To make the paper self-contained, we briefly present PACE algorithm before detailing our implementation of it in a video game and the resulting evaluation.

The *Generalized Experience Management* (GEM) framework (Thue 2015), represents a video-game player as an agent traversing a Markov Decision Process (MDP), collecting rewards (e.g., the feeling of enjoyment) along the way. An AI experience manager is then an AI agent that modifies the MDP's transition function as the game unfolds, in reaction to the player actions. This is a very general framework that encompasses classical and modern narrative and drama managers as well as dynamic difficulty adjustment in video games. We adopt the GEM framework to represent PACE compactly (Algorithm 1).

Algorithm 1: PACE

inputs: narrative space (S, A, p), narrative start state s_1, narrative final states $S_f \subset S$, target emotion curve $\langle \bar{e}^*_t \rangle$

1 $t \leftarrow 1$
2 initialize playstyle inclinations $\bar{i}_1$
3 **while** $s_t \notin S_f$ **do**
4   present narrative state s_t to the player
5   collect player's narrative action a_t
6   update playstyle inclinations $\bar{i}_{t+1}$ from a_t
7   retrieve the relevant goal set G_t
8   compute goal desirability $\bar{d}(G_t)$ from $\bar{i}_{t+1}$
9   compute narrative candidates $\{n_j\}$ from s_t, a_t, p
10   **for** *each* n_j **do**
11   retrieve goal probabilities $\Pr(G_t|n_j)$
12   compute emotions $\bar{e}_j$ from $\Pr(G_t|n_j)$, $\bar{d}(G_t)$
13   compute deviation δ_j of $\bar{e}_j$ from $\bar{e}^*_{t+1}$
14   select the smallest deviation: $j^* \leftarrow \arg\min_j \delta_j$
15   select the next narrative state: $s_{t+1} \leftarrow n_{j^*}|_1$
16   update the game dynamics p so that $s_t \xrightarrow{a_t} s_{t+1}$
17     $t \leftarrow t + 1$

To evaluate PACE operation on a concrete example, we built a narrative-based video game inspired by the classic Romantic ballet *Giselle* (Gautier et al. 1841). In our game the player controls the titular heroine – a talented young ballerina. To illustrate PACE operation, consider a part of the game where at the end of a ballet class the player decides to leave the studio and go to a party. At the party Giselle encounters Beatrice, a rival ballerina (Figure 1, left). It is now up to PACE to select the next section of narrative to be presented to the player. Using the automated planner, PACE computes two possible narrative continuations: in one, the encounter between Giselle and Beatrice escalates to an open confrontation (Figure 1, center). In the other, Giselle apologizes to Beatrice and defuses the situation (Figure 1, right). Which one should be shown to the player?

The answer depends on what the player's emotional reaction to each narrative candidate will be. To decide, PACE predicts the player's emotional reactions and compares them to an author-provided target curve. This process is carried out as follows. First, PACE maintains a model of the player's inclinations towards different playstyles, similar to the approach used by PaSSAGE. For this example, suppose there are three archetypal playstyles: storytelling, showing off and being modest. The author annotates each possible player action in the story with delta values to the playstyle inclinations. Thus, each action the player takes (line 5 in the pseudocode) is used by PACE to update the player model (line 6). In our example, suppose the present value of the player model is $(0.3, 0.7, 0.2)$.

Second, given such a model of the player, PACE infers how desirable certain narrative goals are to him or her. In our example, suppose the author previously identified three goals a player may pursue: maintaining a successful career, avoiding conflict and gaining attention. The author also provided a mapping between the playstyle inclinations and the goal desirabilities. Using the mapping and the player model computed in step one, PACE computes the desirability of the three goals as $(1.79, 0.03, 0.76)$ in line 8.

Third, PACE uses the goal desirabilities and author-provided probabilities of reaching these goals if the player were to go through each of the candidate narratives to predict the player's emotional response. In our example if the confronting-a-rival narrative is chosen the probability of reaching the goal of a successful career will be 50%. The probability of avoiding a conflict will be 0% and the probability of gaining attention will be 70%. The alternative narrative that sees Giselle apologize to Beatrice predicts the player's chances of having a successful career at 40%, avoiding conflict 80% and gaining attention 20%. Using the appraisal model of emotions (Marsella and Gratch 2003), PACE estimates the intensity of the emotions elicited in the player by each candidate narrative. In line with CEMA (Bulitko et al. 2008), PACE models four emotions: hope, joy, fear and distress. For the sake of brevity we limit our example to the emotion of hope which, for the confront-a-rival candidate narrative, is predicted to have the intensity of 1.45 (line 12). The alternative narrative is predicted to elicit the emotion of hope with an intensity of 0.89.

Fourth, PACE compares the predicted values of emotions elicited by the candidate narratives with the target values the author wanted the player to experience at that point in the narrative (line 13). Suppose the author specified that at the current point of the story a player should have an intensity of hope of 0.8. Then the best narrative to present to the player is apologize-to-rival since its predicted value of hope intensity (0.89) is closer to the target 0.8 than the alternative (1.45) (line 14). The first state of the chosen narrative (line 15) is then presented to the player by modifying the game dynamics (line 16).

5 Implementation of PACE in *iGiselle*

To evaluate PACE we created a game testbed called *iGiselle*: an interactive version of the Romantic ballet. In *iGiselle* the player takes control of the titular character and experiences

Figure 1: Giselle encounters Beatrice at a party (left). The encounter can escalate to an open confrontation (center) or be defused with an apology (right).

the narrative through a series of still images, voice overs and music. To further immerse the player in the world of ballet, we forgo a traditional game controller and have the player indicate their narrative choices by assuming dance positions (Figure 2) which are read with Microsoft Kinect.

The multimedia content was developed in two phases. First, working with writers we developed a non-linear narrative graph which allows the player to explore various narratives via choices they will make during the game. The story contained 102 narrative events, 4 choice points, which resulted in 9 distinct narrative trajectories and 10 possible endings, all narrative trajectories lead to the same possible endings. In phase two, we worked with ballet dancers and choreographers, voice actors and recording engineers, photographers and graphic artists to create 162 cell shade images and 270 lines of voice overs.

The narrative graph was encoded as states and actions in the *Planning Domain Description Language* (PDDL) (Ghallab et al. 1998), in order for PACE to be able to generate candidate narratives (line 9 in the pseudocode). We used *Fast Downward planner* (Helmert 2006) which had demonstrated strong performance in planning competitions (Coles et al. 2012). The game interface was coded in C# and linked to the Kinect framework (Microsoft 2013). We implemented a pose recognition module within the framework to read in the player's poses and interpret them as narrative choices. In total, there were 44 people involved in *iGiselle* production which took approximately a year and a half.

6 Empirical Evaluation

To evaluate PACE implemented within *iGiselle*, we ran two formal user studies. For the first user study we divided the participants into two conditions and had them play *iGiselle* with the emotional modeling enabled (the experimental condition) and disabled (the control condition). Upon playing a user study the participants answered 22 questions asking them rate their experience (Figure 3).

The second user study used the same two conditions but all players were now subjected to playing another game as a prelude to their playing *iGiselle*. The survey questions were rephrased so that the subjects' ratings of *iGiselle* would be relative to their ratings of the prelude game (Figure 4).

In both user studies we used a keyboard input instead of Kinect. This was done so that we were able to run up to 20 participants in parallel as we had only a single Kinect sensor.

Assessing the Experience

For each of the following statements, use the scale below it to show how much you agree or disagree with what it says. All these items are related to the interaction you just had the system. When finished, click the "Continue" button below.

The story experience was interesting. *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

The story experience was believable (in its own context) *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

The story experience is consistent with itself (no contradictions in the plot). *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

The story experience experience kept me immersed. *

	1	2	3	4	5	
Strongly Disagree	○	○	○	○	○	Strongly Agree

Figure 3: Sample questions from the user study survey.

6.1 User Study 1

In the first user study there were 294 participants (mean age 19; 148 females, 146 males). For their participation they received a partial course credit for an undergraduate psychology class in which they were enrolled. The participants were divided into two conditions: experimental (149 participants) and control (145 participants). In the experimental condition the subjects played *iGiselle* with their in-game experience managed by PACE. The control condition was the same ex-

Figure 2: *iGiselle* game interface. The player makes his/her narrative choice by assuming one of the three positions shown on the left. The player's current position in visualized with a stick figure in the bottom left window.

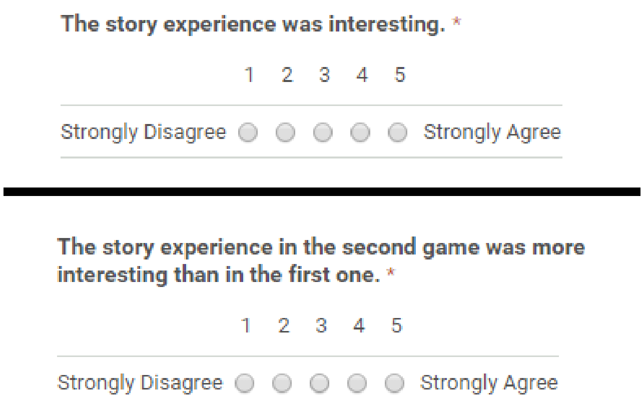

Figure 4: Question difference between study 1 (top) and study 2 (bottom).

cept PACE used a random player model. This was done by disabling line 6 in Algorithm 1 and fixing the inclinations to the final values obtained by a randomly selected participant in the experimental condition. Such setup is known as *yoking* and is meant to approximately equalize the coverage of the player model space in both conditions (Ramirez Sanabria and Bulitko 2014).

Upon completing a game in approximately 40 minutes each participant was directed to fill out a questionnaire to rate his or her *iGiselle* experience. In line with previous work (Thue et al. 2011; Ramirez Sanabria and Bulitko 2014), we used an existing validated instrument for measuring the player's feelings of agency, fun and believability (Vermeulen et al. 2010). Sample questions are listed in Figure 3. The participants reported how much they agree or disagree with each statement on the scale of 1 through 5. Each question was related to one of three categories (the player's feelings of agency, fun and believability). Each category score is the sum of answers to its questions divided by the category's maximum score.

We used the ESD Discordancy test to analyze the scores for any outliers, using the Mahalanobis distance of each data point as the outlier statistic (Zijlstra, van der Ark, and Sijtsma 2011). Outlier detection was done individually for the control and experimental conditions. 11 data points in the control condition and 7 data points in the experimental condition were deemed outliers and removed from further analysis. In line with previous work in the field (Ramirez Sanabria and Bulitko 2014), the remaining data points were further split by gamer and non-gamer based on the average gaming hours per week each participant reported. We used the same values as the previous work, deeming a participant to be a gamer when he/she played at least an hour a week.

Table 1 reports mean category scores. The mean score for fun is slightly higher for the experimental condition for both gamers and non-gamers. The believability is also slightly higher for non-gamers. Neither difference is statistically significant as indicated by a one-way MANOVA ($p > 0.4$ for both gamers and non-gamers) (French et al. 2002).

6.2 User Study 2

The lack of statistical significance in Study 1 may be due to a high variance in the participants' backgrounds. For instance, when answering the question "The story experience was interesting" the participants may have different base-

Table 1: User Study 1.

Player Type	Agency		Fun		Believability	
	Control	**Experimental**	**Control**	**Experimental**	**Control**	**Experimental**
Gamer	0.56	0.53	0.35	0.37	0.60	0.60
Non-Gamer	0.57	0.57	0.37	0.38	0.60	0.64

Table 2: User Study 2.

Player Type	Agency		Fun		Believability	
	Control	**Experimental**	**Control**	**Experimental**	**Control**	**Experimental**
Gamer	0.55	0.40	0.30	0.26	0.62	0.52
Non-Gamer	0.52	0.62	0.33	0.44	0.68	0.65

lines to compare their *iGiselle* experience to. In deciding exactly what "interesting" is, some participants may compare their *iGiselle* narrative experience to a recent commercial video game they played while others may compare it to a piece of fan fiction. In an attempt to calibrate the participants' responses, we ran another user study which used the same two conditions as the first study but had all participants play another game before playing *iGiselle*. Then the survey questions were modified so that the 1-5 ratings of *iGiselle* experience would be relative to this game (Figure 4). We chose PAST (Ramirez Sanabria and Bulitko 2014) for the calibrating experience as it was an interactive narrative experience (albeit without the multimedia of *iGiselle*) and we were granted access to it by its developers.

Due to the timing of this study we were able to recruit only 39 participants (mean age 20; 23 females, 16 males). For their participation they received a partial course credit for an undergraduate psychology class which they were enrolled in. The participants were divided into two conditions: experimental (19 participants) and control (20 participants) which were identical to Study 1 except that they played PAST before *iGiselle* and answered the modified survey questions.

We used the same data analysis procedure. There was only one outlier in the control group. The results are found in Table 2. The mean values for agency and fun are higher in the experimental condition for non-gamers. All the other values for the experimental condition are below the control condition. However, none of the differences reached statistical significance according to the MANOVA ($p > 0.1$ for both gamers and non-gamers).

7 Discussion and Future Work

The results show promise but are not conclusive. Study 1 may have had the participants comparing their *iGiselle* experience to different backgrounds. Study 2 introduced calibration but may have suffered from low numbers of participants. Future work will replicate Study 2 with a larger participant pool to increase statistical power for detecting significant between-group differences.

Furthermore, the difference between the nine distinct narrative trajectories a player can experience in *iGiselle* turned out to be somewhat subtle and may have been missed by some players. For instance, at one point of the story Albert, the ballet director, proposes to Giselle. The player is then presented with three options for Giselle: accept happily, ask for some time to think about it or accept hesitantly. Some participants may not have realized that their answer actually affected the later story, especially as each participant experienced *iGiselle* only once. Future work will rewrite the story to make the impact of player choices more pronounced.

Finally, PACE requires the author to manually specify a mapping from the playstyle inclinations to goal desirability as well as probabilities of achieving various goals given a candidate narrative. Not only is this labour-intensive but the provided values may not be validated. Future work will attempt to procedurally generate some of those parameters. For instance, automated planning and Monte Carlo rollouts can be used to predict probabilities of achieving a goal.

8 Conclusions

PACE is a recent AI experience manager that attempts to keep a player of an interactive narrative video game on an author-provided emotional trajectory. In this paper we presented the first implementation of PACE in a novel narrative-based video game. We then conducted the first formal evaluation of PACE via two user studies with promising albeit inconclusive results.

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