

A Call for Emotion Modeling in Interactive Storytelling

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Abstract

Artificial Intelligence (AI) techniques are widely used in video games. Recently, AI planning methods have been applied to maintain plot consistency in the face of player's agency over the narrative. Combined with an automatically populated player model, such AI experience managers can dynamically create a consistent narrative tailored to a specific player. These tools help game narrative designers achieve narrative goals while affording players a choice. On the other hand, they increase the number of feasible plot branches making it more difficult for the author to ensure that each branch carries the player along a desired emotion arc. In this paper we discuss the problem and call for an extension of experience managers with player emotion models. When successful, interactive narrative can be then automatically produced to satisfy authorial goals not only in terms of specific events but also in terms of emotions evoked in the player.

1 Introduction

Humans have used storytelling as a way of entertainment since our humble beginnings. During human history different ways of telling stories have been practiced. But not only have we focused on how we tell stories but also on how the audience interacts with them. Since stories create an emotional reaction and people react differently to the same situation, there has been an interest in creating story media that allows the audience to influence the story in order to manage their emotional response. An example of this is a pen-and-paper roleplaying game in which a designated human, called the game master, dynamically directs the narrative in response to players' actions. The goal of the game master is to create an enjoyable adventure which frequently requires shaping the story as to evoke a sequence of emotions in the players. The game master does so on the fly, assessing players' emotions and adjusting the narrative in response.

The advent of digital interactive media such as video games offered authors the opportunity to give their audience agency over the narrative without a human game master. While this allows the audience (i.e., now the player) to change the story, it also puts an extra burden on the author who has to implement more than one narrative and make

sure that the narrative remains consistent for any combination of player's actions.

Artificial Intelligence (AI) methods have been proposed to foresee and pre-empt breaks (ruptures) in the story due to player's interaction. AI can help the author maintain consistency of the narrative emerging from player's interactions with the story world. However, such AI experience managers may not be able to guarantee that the emergent narratives also evoke desired emotions from the player. In this paper we propose extending the AI techniques with explicit models of player's emotions and using such to ensure not only plot consistency but also desired emotional response from the player.

2 Problem Formulation

The ability of the audience to affect the story they are experiencing is simultaneously a blessing and a curse. It is a blessing as it allows the audience (i.e., the player) to feel agency and at least partial ownership of the story. For instance, in the *Mass Effect* trilogy, the players have developed their own Shepard by making choices across the three games. They felt strongly about their ability to affect the story and the universe (Orland 2012).

Player agency is a curse as it puts a significant burden on the game developers who have to anticipate possible player actions and make the game world respond sensibly to such. As the number of stories can increase exponentially with each choice available to the player, the developers have used a number of plot-shaping techniques (e.g., narrative bottlenecks or independent subplots) to keep manual content generation tractable. Recent research automates some of the plot generation aspects using techniques from AI planning (Riedl et al. 2008). While such approaches help the developers ensure consistency in the game world in response to player actions, they can potentially put the developer out of touch with the emotional side of their game. Indeed, the combinatorial explosion of different story lines afforded by more efficient story generation approaches can make it hard for the developer to ensure that all/most stories enabled in the game are still emotionally impactful.

Even if such emotional impact quality assurance at the development time could be done effectively, there is an additional problem that different players can have different emotional responses to the same narrative. This is similar to

the problem of ensuring that players have fun while playing the game — some players have more fun looting dungeons while others may prefer developing their relationships with their party members. Research on interactive storytelling has been addressing this by creating an explicit model of player’s inclinations and changing the narrative to cater to such inclinations (Thue et al. 2007).

In this paper we propose to equip AI experience managers with explicit player emotion models. Such models will track player’s emotional response as he or she is playing the game and modify the narrative dynamically to keep the player on an author-specified emotion arc. This is, in effect, a generalization of the “emotional intensity” tracking and adjustment problem, tackled by the AI Director of Valve’s *Left4Dead* (Booth 2009). We propose to consider other types of emotions and, as a first step, will focus on fear, distress, hope and joy (Marsella and Gratch 2003).

We will consider such an automated emotion-modeling experience manager successful if it increases the likelihood of the player experiencing the emotions the game designer intended them to, at the cost of a moderate increase in the development time (to mark up game narrative with emotion annotations).

3 Related Work

The two parts of our problem, emotion models and narrative shaping, have been independently addressed. In particular a number of computational models of emotions have been proposed over the years (Lin, Spraragen, and Zyda 2012). For narrative-driven games where player often pursues specific goals, appraisal-based models may be particularly relevant (Lazarus 1991). Such models compute player’s emotional state as a result of the interaction between player’s goals and their current narrative state. For instance, a possible failure induces fear whereas a definitive failure causes despair. A popular appraisal-based model used by computational models is OCC (Ortony, Clore, and Collins 1990). This model is capable of represent up to 22 different emotions in respect to reactions to situations around goal oriented events. The OCC model has been used by several systems (Gratch 2000; Aylett et al. 2005; 2007; Rank and Petta 2005; Cavazza et al. 2009). For instance *Émile* (Gratch 2000) computes the probability of agent’s success with respect to their current intentions and uses that information to estimate agent’s emotional state. Another choice is *EMotion and Adaptation* (EMA) (Marsella and Gratch 2003) which has been used to infer character emotions and map them to character’s appearance (Kenny et al. 2007). Such models of emotions can be a part of the solution to the problem we are tackling in this paper since the player’s estimated emotion state can be used to select the next bit of narrative.

The other part of our problem is narrative shaping which has also been studied extensively. The *Automated Story Director* (ASD) (Riedl et al. 2008) uses an AI planner to build a narrative, taking a formal description of the universe and authorial goals as the input. ASD also considers how a player might rupture the exemplar narrative and generates alternate

narratives. An extension of ASD is a system called *Player-specific Automated Storytelling* (PAST) (Ramirez and Bulitko 2012) which combines the AI planner of ASD and the player model of *Player-Specific Stories via Automatically Generated Events* (PaSSAGE) (Thue et al. 2007; 2011). The player model is used to repair a rupture in a way specifically tailored to the particular player. Both ASD and PAST attempt to ensure that event-level authorial goals are fulfilled in spite of player’s interaction. However, neither explicitly considers player’s emotions or whether authorial goals at the level of emotion dynamics are fulfilled.

Player’s emotions had been considered in several research projects. A seminal example is *Façade* (Mateas and Stern 2003). Its drama manager creates a narrative that follows an author-specified tension curve. Each plot point in the system is manually annotated with a tension value beforehand. Then on-line, the drama manager chooses a plot point whose tension value will keep the unfolding story on the target tension curve. However, the tension values are associated with the plot points and do not track tension of a given player. In other words, every player is assumed to have the same emotional reactions to story events. Such an assumption is a necessity in non-interactive storytelling media such as motion pictures where redundant elements (music, lighting, etc.) are used in an attempt to coral the audience members to experience the same emotion (Tan and Fasting 1996; Smith 2003). This is not necessary in interactive storytelling where the computer can, in principle, tailor its story to each individual audience member.

More recent work investigated computing suspense values for a given narrative (O’Neill and Riedl 2011). While this approach can be useful for an emotional quality assurance at the development time, it is presently limited to a single-dimensional emotion space (suspense) and, like *Façade*, does not model individual player response.

The problem presented in this paper was addressed by the AI Director in the commercial video game *Left4Dead* (Booth 2009). The first-person shooter had four players working together in a zombie-survival setting. The AI Director used observable variables for each player (e.g., their avatar health level, their shooting accuracy, etc.) to derive an estimate of the players’ current “emotional intensity” level. The four predicted values (one per player) were then used to modulate zombie horde size, composition and placement in a way as to keep each of the four players on its emotional roller coaster (a sinusoidal curve in the tension space). While groundbreaking, the AI Director was limited to modeling only tension and making changes to gameplay only (as opposed to global narrative).

4 Proposed Approach

In traditional storytelling in books and movies, the author/director dictates every and all details of the story, down to every word and every camera angle. Interactive storytelling in video games gives up the authorial control for player’s agency. A principled approach is to represent stories as formal plans. The author can then specify their narrative in terms of domain constants, planning operators (with pre-conditions and effects) and the goal states. An

AI planner can then create a sequence of events leading the player from the initial state to a goal state (Riedl et al. 2008; Ramirez and Bulitko 2012).

We propose to extend this abstraction process. Specifically, instead of specifying the goal states in terms of grounded predicates (e.g., (eat wolf granny) in *The Little Red Riding Hood*) the author would specify a desired emotional event (e.g., (surprised player)) which can be reached with the wolf disguised as the granny or by the granny turning the wolf into a vegan. Thus, similarly to the ASD, we propose that the author specifies their narrative domain in a formal planning language but also uses a number of emotion-related predicates to describe a sequence of emotional states they want the player to go through (i.e., the emotion arc). An AI planner, working on-line will then plan a sequence of events to put the player through the desired emotional states. As the player follows the resulting narrative, his/her actions will be used to update their emotional state. If the player fails to respond with a desired emotion, the planner will automatically modify the narrative in an attempt to keep them on the author-supplied emotion arc.

4.1 Proposed Implementation

We are implementing the experience manager in phases. We started with the experience manager of PAST that combines the AI planner of ASD and the player model of PaSSAGE. We are extending PAST in two ways. First, each narrative event is to be annotated with a vector showing changes to player emotional state. This annotation will be similar to the one used by *Façade*, but in our case it is not a single number representing the tension of the event, but a vector where each element represents how the event will affect the emotion it represents. For instance, the event “huntsman kills the wolf” can be annotated with these changes to the player’s emotional state: (F:0, D:0, H:0, **J: 0.5**) showing that the player’s joy goes up by 0.5.

As we run our experiments we will look for correlation between the player types and emotions evoked by the events. For instance, we may find that a violent confrontation is likely to heighten fear in a tactician but joy in a fighter. If we find such a correlation we will extend the emotional vector to become a matrix containing an emotion vector for each basic player type. Then, when selecting a repair for a rupture in the narrative, our experience manager will use the player’s model (i.e., the play-style inclinations) to compute expected updates to player’s emotional state.

To illustrate, consider a player whose player-type inclinations (i.e., fighter, tactician, method actor, storyteller, power gamer) have been inferred to be:

$$(0.7 \ 0.1 \ 0 \ 0.3 \ 0.1). \quad (1)$$

Suppose such a player just witnessed the event “huntsman kills the wolf”. The event is annotated with the following matrix:

$$\begin{pmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0.6 & 0 & 0 & 0 \\ 0.8 & 0 & 0.2 & 0 & 0.1 \end{pmatrix} \quad (2)$$

where the rows represent the four modelled emotions (fear, distress, hope and joy) and the columns correspond to the five player-type inclinations. For instance, the 0.6 represents that a player with a tactician inclination of 1 will receive an increase of 0.6 to the emotion of hope. The model update is then computed as a matrix product of the annotation matrix (2) and the player-type vector (1):

$$\begin{pmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0.6 & 0 & 0 & 0 \\ 0.8 & 0 & 0.2 & 0 & 0.1 \end{pmatrix} \times \begin{pmatrix} 0.7 \\ 0.1 \\ 0 \\ 0.3 \\ 0.1 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0.06 \\ 0.57 \end{pmatrix}.$$

The resulting vector of updates to the emotion model will increase the player’s hope by 0.06 and player’s joy by 0.57.

In the second phase, we propose to eliminate manual annotations by estimating player’s emotional state procedurally, with a computational emotion model. We will start with the subset of EMA (Marsella and Gratch 2003) used within the CEMA system (Bulitko et al. 2008) to procedurally compute player’s fear, distress, hope and joy. The system will be enhanced so that it is able to determine the player’s goals, it will use this information along with the emotion model of the player to determine which event to select to keep the player in the desire emotion curve.

5 Future Work

Our call for explicit emotion modeling and its use for experience management in interactive narrative needs to be implemented. We currently have an early implementation proposed in the previous section running with a short interactive version of *The Little Red Riding Hood* story and are working on a more complex setting of ballet stories. Once the implementation is complete, it will be evaluated against PAST in a user study.

Future work will also attempt to eliminate any authorial goals expressed in terms of events (e.g., wolf eats Red) and have the author specify only the emotion arc and the narrative domain (e.g., characters, their actions, lore, etc.) in which the story takes place. It will be interesting to investigate the extent to which giving AI such authorial autonomy can produce engaging and consistent narratives.

6 Conclusions

Interactive storytelling gives the audience an ability to change the narrative, making author’s job more difficult. AI planning systems come to rescue by dynamically planning narrative events to satisfy authorial goals. While with their help the author can ensure that the narrative experience remains consistent despite player’s actions, the emergent narrative may evoke an emotional response substantially different from what the author desired.

In this paper we called for extending AI experience managers with an explicit model of emotions. Such a model will be updated dynamically during the gameplay from observed player actions. The AI planner within the experience manager will then use the model to shape the narrative in order to keep the player on the author-specified emotion arc.

References

- Aylett, R. S.; Louchart, S.; Dias, J.; Paiva, A.; and Vala, M. 2005. FearNot!—an experiment in emergent narrative. In *Proceedings of Intelligent Virtual Agents*, 305–316. Springer.
- Aylett, R.; Vala, M.; Sequeira, P.; and Paiva, A. 2007. FearNot!—an emergent narrative approach to virtual dramas for anti-bullying education. In *Virtual Storytelling. Using Virtual Reality Technologies for Storytelling*. Springer. 202–205.
- Booth, M. 2009. The AI systems of Left4Dead. In *Keynote, Fifth Artificial Intelligence and Interactive Digital Entertainment Conference (AIIDE09)*.
- Bulitko, V.; Solomon, S.; Gratch, J.; and van Lent, M. 2008. Modeling culturally and emotionally affected behavior. In *Proceedings of Artificial Intelligence and Interactive Digital Entertainment Conference (AIIDE)*, 10–15.
- Cavazza, M.; Pizzi, D.; Charles, F.; Vogt, T.; and André, E. 2009. Emotional input for character-based interactive storytelling. In *Proceedings of The 8th International Conference on Autonomous Agents and Multiagent Systems-Volume 1*, 313–320. International Foundation for Autonomous Agents and Multiagent Systems.
- Gratch, J. 2000. Émile: Marshalling passions in training and education. In *Proceedings of the fourth international conference on Autonomous agents*, 325–332. Association for Computing Machinery (ACM).
- Kenny, P.; Hartholt, A.; Gratch, J.; Swartout, W.; Traum, D.; Marsella, S.; and Piepol, D. 2007. Building interactive virtual humans for training environments. In *Proceedings of The Interservice/Industry Training, Simulation & Education Conference (IITSEC)*, volume 2007. NTSA.
- Lazarus, R. S. 1991. *Emotion and adaptation*. Oxford University Press New York.
- Lin, J.; Spraragen, M.; and Zyda, M. 2012. Computational models of emotion and cognition. In *Advances in Cognitive Systems 2*.
- Marsella, S., and Gratch, J. 2003. Modeling coping behavior in virtual humans: don't worry, be happy. In *Proceedings of the second international joint conference on Autonomous agents and multiagent systems*, 313–320. Association for Computing Machinery (ACM).
- Mateas, M., and Stern, A. 2003. Façade: An experiment in building a fully-realized interactive drama. In *Proceedings of Game Developers Conference, Game Design track*, volume 2, 82–106.
- O'Neill, B., and Riedl, M. 2011. Toward a computational framework of suspense and dramatic arc. In *Affective Computing and Intelligent Interaction*. Springer. 246–255.
- Orland, K. 2012. Protests over ending of Mass Effect 3 show fan investment in story control. <http://arstechnica.com/gaming/2012/03/protests-over-ending-of-mass-effect-3-show-fan-investment-in-story-control/>.
- Ortony, A.; Clore, G. L.; and Collins, A. 1990. *The cognitive structure of emotions*. Cambridge university press.
- Ramirez, A., and Bulitko, V. 2012. Telling interactive player-specific stories and planning for it: ASD + PaSSAGE = PAST. In *Proceedings of Eighth Artificial Intelligence and Interactive Digital Entertainment Conference (AIIDE)*, 173–178.
- Rank, S., and Petta, P. 2005. Appraisal for a character-based story-world. In *Proceedings of Intelligent Virtual Agents*, 495–496.
- Riedl, M. O.; Stern, A.; Dini, D.; and Alderman, J. 2008. Dynamic experience management in virtual worlds for entertainment, education, and training. *International Transactions on Systems Science and Applications, Special Issue on Agent Based Systems for Human Learning* 4(2):23–42.
- Smith, G. M. 2003. *Film structure and the emotion system*. Cambridge University Press.
- Tan, E. S., and Fasting, B. T. 1996. *Emotion and the structure of narrative film: Film as an emotion machine*. Lawrence Erlbaum Associates, Inc.
- Thue, D.; Bulitko, V.; Spetch, M.; and Wasylishen, E. 2007. Interactive storytelling: A player modelling approach. In *Proceedings of Artificial Intelligence and Interactive Digital Entertainment Conference (AIIDE)*, Stanford, CA, 43–48.
- Thue, D.; Bulitko, V.; Spetch, M.; and Romanuik, T. 2011. A computational model of perceived agency in video games. In *Proceedings of Artificial Intelligence and Interactive Digital Entertainment Conference (AIIDE)*, 91–96.