Using Facial Expressions for Personalised Gaming

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Artificial intelligence (AI) in games ideally provides satisfactory game experiences for all players, regardless of gender, age, capabilities, or experience [4]: it personalises games, i.e., the game experience is continuously tailored to fit the individual player. A major challenge in game personalisation is how to build and estimate a model of how game elements affect the player. In particular, we are interested in which elements have a positive effect on the *affective state* of the player. However, effectively estimating information about this affective state from the information that is available in online gameplay is a major challenge. In online gameplay only implicit feedback on the appropriateness of the personalisation actions is available, i.e., the AI can only observe the player interacting with the game, while not being provided with labels on the player's *affective state*, and explicitly asking the player is too intrustive for the player to fully enjoy the game.

In this demo, we show how game personalisation techniques can leverage novel computer vision-based techniques to *unobtrusively* infer player experiences automatically based on facial expression analysis. Specifically, we employ algorithms for tailoring the affective game experience to the individual user that (1) leverages the proven INSIGHT facial expression recognition SDK as a model of the users affective state[1], and (2) employ this model for guiding the online game personalisation process. Specifically, we use the emotion *anger* versus *happiness* (or *neutral*) to measure user experience, and adapt the game accordingly. These algorithms have been previously published in [2].

In this demo, participants can play the video game INFINITE MARIO BROS, while it is being personalised using an AI. The AI typically decreases challenge levels of certain game elements when the face of the user shows anger, and typically increases challenge levels of these game elements when the face of user is neutral or looks happy.

1 Approach

In this section, we describe the algorithmic approach that we use for the demonstration, as previously published in [2], which builds on the perspective that computer vision techniques can provide to automatically infer gameplay experience metrics. The first step in doing so is to recognize facial expressions. This is a well-studied domain in computer vision with techniques that can reach a high level of accuracy and robustness. E.g., Buenaposada et al. [3] have reported an 89% recognition accuracy on average in video sequences in unconstrained environments with strong changes in illumination and face locations.

In this demonstration, the challenge level of a game is balanced by adapting the *content* that is placed within the game environment dependent on facial expression analysis, i.e., we use procedural content generation for tailoring to the individual player [1, 2]. To this end, we use an AI to assess, *online* and *unobtrusively*, which adaptations are required for optimizing the individual players experience while the game is in progress. We use a typical video game: INFINITE MARIO BROS[2] — an open-source clone of the classic video game SUPER MARIO BROS. In particular, we use the 2011 Mario AI Championship game engine of INFINITE MARIO BROS, with two further enhancements [1]. First, it now is able to procedurally generate segments of Mario levels while the game is in progress, as illustrated in Figure 1. Second, we can now inject short chunks of specific game content: (1) a straight chunk, with enemies and jumpable blocks, (2) a hill chunk, also with enemies, (3) a chunk with tubes and enemy

[1] http://sightcorp.com/

[2] http://www.mojang.com/notch/mario

plants, (4) a jump, and (5) a chunk with cannons. Each type of chunk can have six distinct challenge levels, expressed as a parameter value in $[0, 5]$. The challenge level of the chunk increases monotonically with the parameter value. In online gameplay, the only action that the personalisation AI can take is to output a vector of five integers (chunk parameters on the interval $[0, 5]$) to the procedural process that generates the next level segment. While this action space is relatively small, its resulting expressiveness ranges from extremely easy to nearly impossible level segments.

As input, the personalisation AI uses classifications of the human players facial expressions. In order to map these classifications to appropriate in-game challenge levels, we employ a Gradient Ascent Optimisation (GAO) technique [2], for optimising the challenge levels for each chunk type in the game, such that human interactions with the content yield affective stances that we consider desirable (i.e., happiness), while minimising affective stances that we do not consider desirable (i.e., neutrality and anger).

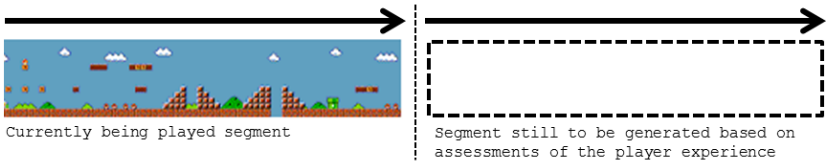

Figure 1: *Generating segments for INFINITE MARIO BROS.*

After a game segment has been completed by the human player, the probability-distribution vector of the measured emotional stances are retrieved for each individual chunk. The emotions taken into consideration for the present experiments are (1) neutrality, (2) happiness, and (3) anger. When a game segment is finished, the emotion vectors – of each individual chunk – of the recently played (finished) segment, plus the previously completed segment, are fed into the algorithm. For each emotion that is taken into consideration (neutrality, happiness and anger), the difference between its current and previous iteration value is obtained. Next, the maximum of these three differences is determined. Since the three emotions are equally weighted, the maximum value calculated could be considered as the "most significant" change in emotional status of the user between two game segments. We map this emotional change to an action of the AI, i.e., a change in challenge level for the chunk types of the segment that has just been completed by the player on the interval $[-5, 5]$. (For chunks that did not appear in the last segment, we do not change the challenge level.) In practice, the algorithm will increase the game challenge level if the probability estimate of an emotion is higher in timestep t compared to $t - 1$.

A pilot study [2] indicated that this approach decreases specific challenge levels in the face of user anger, and increases specific challenge levels in the face of user neutrality or happiness as expected, and appears stable in the face of classification noise. A significant majority of participants in the study prefered the personalised system over a non-adaptive system, except in cases when anger (frustration) of the human participants was not expressed in terms of facial expression, but in terms of hand gesturing, verbal actions, or head movements that prevented facial expressions from being assessed accurately.

2 Demo

In the demo, participants can play INFINITE MARIO BROS., while the personalisation AI adapts the game on the basis of the facial expressions of the participant. The demo requires a computer with a 1.6GHz dual core processor or better, 2GB RAM, a webcam with a resolution of at least 640×480, and an active internet connection. The lighting is controlled by applying a stable light source, and screens around the player in order to avoid sudden fluctiations that might happen due to passing spectators.

References

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