Towards Player's Affective and Behavioral Visual Cues as drives to Game Adaptation

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Abstract

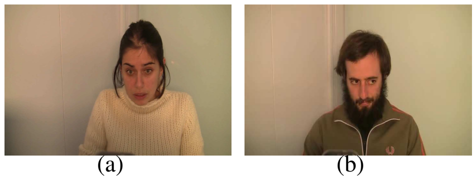
Recent advances in emotion and affect recognition can play a crucial role in game technology. Moving from the typical game controls to controls generated from free gestures is already in the market. Higher level controls, however, can also be motivated by player's affective and cognitive behavior itself, during gameplay. In this paper, we explore player's behavior, as captured by computer vision techniques, and player's details regarding his own experience and profile. The objective of the current research is game adaptation aiming at maximizing player enjoyment. To this aim, the ability to infer player engagement and frustration, along with the degree of challenge imposed by the game is explored. The estimated levels of the induced metrics can feed an engine's artificial intelligence, allowing for game adaptation.

Keywords: Games Artificial Intelligence,Head Pose Estimation,Player State Estimation

1. Introduction

Playing computer games is an activity enjoyed by millions of people worldwide, for thirty or even more years now. Since the basic controls of interaction in the 80's, a lot has changed today, with one of the latest achievements of today's technology that of gesture recognition platforms. The player can just interact with the game, in a completely non-intrusive way, while his body itself plays the role of the game controls. Within this view, the path to affective computing (Picard, 1997) in game-playing has opened, showing the way to using, not only one's gestural movements as input to game control, but his behavioral and affective state. Human-Computer interaction (e.g. human-agent communication), within in this view, is beginning to take advantage of systems consisting of sensors capturing affective and physiological data (Picard, 1997; Castellano et al., 2009; Kapoor et al., 2007). Player behavior towards particular game events or during whole sessions of gameplay can become a useful source of information for the game's Artificial Intelligence (AI), so that it adapts itself to player's affective state. Within this frame, heart rate measurements, respiration, pressure on the mouse, posture in a chair, blood or brain oxygen levels have been shown to be valuable behavioral indicators used as inputs to the AI of a game, so that player's enjoyment is optimized.

In search for features correlated with the notion of engagement, frustration and challenge in games, a lot of works have been proposed in bibliography (van den Hoogen et al., 2008; Sanghvi et al., 2011) using expressive body and facial movements, as well as a multitude of sensorial cues (Kapoor et al., 2007; Sykes and Brown, 2003) to inform an immersive game environment about player's actual cognitive and affective state. Estimating moments of particular behavioral cues (see Figure 1) using non intrusive means can be a valuable source of information for the game experience: First, the player is not disrupted by intrusive mechanisms which might interfere with the whole experience. Furthermore, cognitive and affective features can be transferred automatically, not necessitating that the player interrupts gameplay in order to report these data, nor that he has to recall his perception on each separate gameplay experience. The advances on computer vision techniques under non-pretending conditions have allowed the proposal of a few techniques incorporating notions such as body movements (Castellano et al., 2009; Sanghvi et al., 2011) head motion and eye gaze (with eye gaze still necessitating specialized hardware (Jennett et al., 2008)).



(a) (b)

Figure 1: Players' visual reactions towards certain events taking place during gameplay

In this paper, we address the issue of estimating those game events that, in conjunction with specific player characteristics and behavioral cues, could trigger specific affective and/or cognitive states towards a gameplay session. Taking into account previous research (Castellano et al., 2009; Sanghvi et al., 2011), players' intensity of movement, modelled, here, as movements of the head, was correlated to specific events and player characteristics. More in particular, user reported levels of challenge (how challenging the player would find a game he just finished, with regards to his/her own experience and taste), frustration (how frustrating a game was found, usually due to large obstacles as, most players, confessed) and engagement (how much players actually enjoyed a game they just finished playing) are mapped to visual and personal features. The proposed research is in line with Csikszentmihalyi's flow theory (Csikszentmihalyi, 1997), i.e. game features that would characterize a game as challenging are combined with player's

expressed arousal (during whole game sessions or when specific events occur) and self reported skill level, in order to infer engagement. Taking the above as input to a clustering algorithm, the system attempts to define possible moments of high engagement, frustration, and challenge, in an attempt to work towards extending the model of Csikszentmihalyi, by correlating the notions of engagement and frustration (apart from challenge) to experience models and introducing demographic and visual behavior-related features to profiling schemes. The results of the proposed system are promising, in the sense that they could contribute to the design of a self-adaptive game, aiming at maximising the feeling of engagement during gameplay.
The structure of the paper is organized as follows: Section 2. presents the game platform and the data acquisition procedure, respectively, while Section 3. gives an analytical description and discussion on experiments conducted under personalized and generalized protocols. Section 4. concludes the paper.

2. Dataset Acquisition

The testbed platform game used for our study is a modified version of Markus Perssons Infinite Mario Bros, which is a public domain clone of Nintendo's classic platform game Super Mario Bros. The original Infinite Mario Bros and its source code is available on the web [1]. The gameplay in Super Mario Bros consists of moving the player-controlled character, Mario, through two dimensional levels. Mario can walk, run, duck, jump, and shoot fireballs. The main goal of each level is to get to the end of the level. Auxiliary goals include collecting as many coins as possible, and clearing the level as fast as possible. While implementing most features of Super Mario Bros, the stand out feature of Infinite Mario Bros is the automatic generation of levels. Every time a new game is started, levels are randomly generated. In our modified version, we concentrated on a few selected parameters that affect gameplay experience.
Volunteer players in Greece and Denmark were asked to play a series of different game sessions. Players were between 23 and 39 years old (average $\simeq 29yrs$), while conditions were typical of those of an office environment (see Figure 2). After each game, players were asked to assess the degree of engagement, frustration and challenge associated with the gameplay. The selection of these states is based on earlier game survey studies (Pedersen et al., 2010) and the intention to capture both affective and cognitive/behavioral components of gameplay experience (Yannakakis and Togelius, 2011). Furthermore, self-reporting had to be kept as limited as possible, so that experience disruption was minimized. The assessments were given in the form of ratings from 0 to 4. The analysis presented in this paper is based on 36 players playing 240 games. A more analytical description of the experimental procedure and data collection protocol can be found in (Shaker et al., 2011), while the full dataset is available at http://sirenproject.eu. Players' recorded video sequences were analyzed using the methodology reported in (Asteriadis et al., 2009). This algorithm offers real-time estimates of head rotation. In this paper, we used the first derivative of head rotation vector (horizontal and vertical) norm, as an indicate of head motion "quantity".

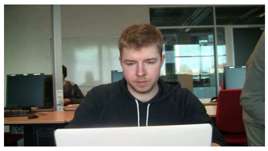


Figure 2: Typical example frame of the collected dataset.

While playing the game, different player and game-content actions, as well as their corresponding time-stamps were recorded. Player's visual behavior was estimated in the following cases: *Average head motion per game, Head motion when player loses, Head motion at stomping on an enemy to kill him, Head motion when player is about to make a critical move*. Furthermore, profile characteristics considered here were the following: *Whether player is a frequent gamer, How much time they spend playing games on a weekly basis, Age,* and *Whether they had played Super Mario before.* Most players (30 out of 36) said that they were at least a little familiar with Super Mario, while 25 players declared themselves as occasional or frequent gamers. The above reports appear to be quite independent of age, though.
The above parameters are used as inputs for predicting user affective and cognitive state (engagement, frustration, challenge) experienced after each game session.

3. Experiments

3.1. Player independent training

For estimating user state (engagement, challenge, frustration), different combinations of the above features were tried. Each player's annotations were averaged on a per game basis, normalized from 0 to 1 and further classified to labels (challenged-not challenged, engaged-not engaged, frustrated-not frustrated). Table 1 gives an overview of F-measures and overall accuracies achieved for different combinations of features, for all game sessions, following a leave-one-player-out protocol, utilizing Fuzzy 3-NN clustering (Keller et al., 1985). The features used for inferring each state have been decided after a feature selection method, so that estimation accuracy is maximized. Mean Head Motion is the average head movement (expressed as the first derivative of head rotation) throughout all sessions for every person, while Mean Lose-Events Head Motion, Mean Head Motion at killstomp (killing enemies by stomping them), Mean Head Motion at Move Start are the corresponding average values per person for a period of 10 frames before and after the corresponding events. Before using the algorithm all data were normalized from 0 to 1. Typical player reactions when losing can be seen in figure 3.
The above results indicate that visual motion behavior can be a strong indicate for all three affective and cognitive states. More specifically, average head motion appears to be an indicate for distinguishing between challenging and non-challenging games. Challenging interactions increase

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

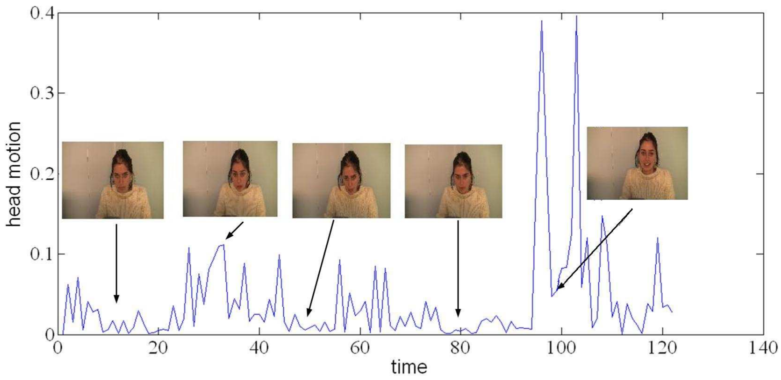


Figure 3: Player visual behavior during gameplay. In this session, Super Mario was killed in seconds $\simeq 32$ and $\simeq 100$.

Table 1: F-measures and accuracy achieved for different combinations of behavioral features and player details. 1's correspond to feature used for estimating the behavioral state of the corresponding column, and 0's mean that the corresponding feature has not been used.

	Challenge	Frustration	Engagement
Mean Head Motion per Session	1	0	0
Mean Lose-Events Head Motion	0	1	0
Mean Head Motion at Killstomp	1	1	1
Mean Head Motion at Move Start	1	1	0
Played Before	1	0	0
Time of playing per week	0	0	1
Playing Games	0	1	1
Age	0	1	1
F-measure / Accuracy	0.73/69%	0.71/74%	0.70/71%

the levels of arousal (Gross and Levenson, 1993) and the player externalizes this experience by high levels of overall motion. Head Expressivity when a critical move is about to take place appeared to be low when players felt challenged by the game, probably due to the fact that they were trying to concentrate on the critical move. This characteristic would be mainly associated with games provoking high levels of challenge, which usually implies that the player felt at risk of losing and momentary increased levels of concentration were vital. On the contrary, frustrating games would mainly be associated with high motion expressivity at the start of critical moves. High expressivity when stomping to kill an enemy appears to be positively correlated with high levels of challenge and frustration, although engaging games showed the contrary.

Having prior experience in Super Mario also appears to play a role for the cases of frustration and engagement. Our results indicate that general gamers would, more frequently, declare that no engagement or frustration was experienced, and that may be attributed, probably, to their game habits. Similar is the case for younger players, probably due to their exposure to different kinds of games (see Fig. 4). However, those players declaring that they had never played Super Mario before had more chances of saying that they felt challenged by the game, than the experienced ones.

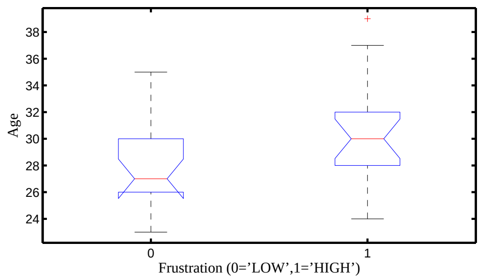


Figure 4: Box plot of medians with comparison intervals of frustration levels as function of age.

3.2. Player dependent training

Estimating player state based on his or her *own* behavioral characteristics is of primary importance for game adaptation. Different players pose different expressions, motion patterns and expressivity characteristics when reacting to the same stimuli. This idea triggers experimentation on building on individual profiles with aim at a personalized, profile-aware game, capable of discriminating between individual behavioral and affective cues. We used a subset of the players of the dataset described above, so that each of them played at least 8 games. We tested for each gameplay of each player, separately, using as knowledge-base only data from his own games, and we considered as input, behavioral cues from head expressivity. It was noticed that classifying between games provoking high and low levels of engagement gave the best results (F-measure=0.61, accuracy=82%).

4. Discussion and Conclusions

This paper has explored the possibility of using visual behavior during certain game events, as well as player's profile information, as predicates of behavioral, cognitive and emotional states. Our preliminary results show that subsets of features can be utilized during gameplay, in order to elicit hidden information regarding user state and, thus, use it for game adaptation. Experimentation on a personalized level reveals that there is also potential for individualized game adaptation. However, these experiments need to be further expanded with more data, in order to be able to generalize across a much richer set of subjects. Moreover, ideally, the number of men and women in the dataset should be balanced (in this paper, out of 36 participants, only 8 of them were women). Furthermore, parameters related to game difficulty should also be taken into account in conjunction with visual and profile characteristics, as a metric for game challenge. It is also worth to point out that the moderate prediction accuracies obtained can be most likely due to the limitations of the rating reporting scheme considered in this paper. Self-reported ratings are affected by a number of effects including culture, personality and several types of scaling biases. Moreover, recent findings suggest that rating reporting schemes yield higher order and inconsistency effects when compared to ranking reporting schemes (such as pairwise preferences) (Yannakakis and Hallam, 2011). Future work will, therefore, focus on predicting ranking self-reports of the players — which are existent in the dataset but not used in this study — via the use of preference learning (Shaker et al., 2010).

Future research will focus on evaluating a closed-loop system, i.e., perform game adaptation based on the inferred player state during gameplay, in order to explore the practical usability of the above findings for minimizing frustration and maximizing player engagement. Special focus will also be placed on analyzing cultural and gender differences, as components of player's personal profile.

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