Measuring Affective, Physiological and Behavioural Differences in Solo,

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Abstract. In this paper, we aim to measure affect and behaviour indicators of players to understand how they feel in different play modes and how games could be improved to enhance user experience, immersion and engagement. We analyse the affective states in sets of two users playing a Wii video game in three play modes: solo, competitive and collaborative. We measured their physiological signals and observed the non-verbal behaviours to infer their affective states. Although other studies have looked at these signals in gaming, this work focuses on the differences between the three play modes aforementioned. Our results show that: (1) Players experience similar levels of arousal during both solo and collaborative play modes; (2) players' heart rates are significantly correlated during the competitive mode but not during the collaborative one; and (3) heart rate variability is a good indicator of engagement when playing video games. AQ1

Keywords: Affective gaming · Physiological signals · Non-verbal behaviour

1 Introduction

User affective states play a major role in immersive and engaging game experiences by influencing user experience and satisfaction [1]. As the present focus of game design is to increase the degree of immersion, enjoyment or simply to provide a pleasurable experience to the player, it is important to understand how players feel when interacting with the game and how different game events change their affective states. The recognition of the player's affective states brings exciting possibilities to gaming, from controlling games using physiological signals (biofeedback) to adapting it according the player's emotions (affective feedback) [2,3]. Gilleade et al. [1] propose that affective gaming should be used to keep the player engaged and motivated to play. For example, if the player gets bored,

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the game should increase the difficulty level to keep him engaged, but if he gets frustrated or too stressed, the game should be easier or give hints about how to progress. Current research in affective gaming is mainly focused on affective feedback, trying to enhance user experience by adapting the game to the player's affective state. However, not many studies have explored the effects evoked by video games in different play modes such as competitive, collaborative or solo.

This study is interested in investigating how collaborative and competitive game modes affect the player interactions and whether we can assess this by measuring players' physiological and behavioural signals in different play modes. We present a pilot study which explores the physiological and behavioural differences between sets of two co-located users playing a Wii video game in three play modes: solo (one-vs-computer), competitive and collaborative. Our analysis show that (1) heart rate is a good measure for assessing arousal and heart rate variability for assessing player engagement; (2) competitive play evokes higher arousal than the other two play modes; and (3) players experience a similar arousal level when playing solo and collaboratively.

2 Related Work: Affective and Multiplayer Gaming

The recognition of affective states is key for any affective computing application. The classification of affect can be a challenging task due to subjective cognitive and physiological reactions to external stimulus, since not everybody responds in the same way to different events. The most common classification approach is the two-dimensional arousal-valence [4]. The first dimension, arousal, maps the activation level and can be measured through the physiological modality such as cardiac activity, using electrocardiogram (ECG), or sweating level, measured with Galvanic Skin Response (GSR) [3,5]. The second one, valence, describes the degree of pleasantness of the affective state, frequently measured by looking at the visual or audio modality, including facial expressions, non-verbal and verbal behaviour [2]. Savva and Bianchi-Berthouze [6] used a motion capture system to analyse the affective states of the users playing a Wii tennis game. Using a Recurrent Neural Network algorithm, they grouped the affect into four different categories: happiness, concentration and low and high intensity negative emotion. The results showed recognition accuracy of 57 %.

The physiological signals related to the player's affective state have been mostly used in affective gaming in two different ways, either to directly control the game (biofeedback) or to indirectly adapt it to the player (affective feedback) [2,3]. *Relax-to-win* [7] is a biofeedback game where the player's arousal, measured by the GSR, controls the speed of a racing dragon, decreasing the dragon's pace when the arousal level increases so the player who relaxes more quickly wins the race. The game *Left 4 Dead 2* [8] was transformed into an affective feedback game, where the player's stress level was monitored by measuring arousal through heart rate. The game automatically adapted to the player's affective state, changing certain elements such as music loudness if the player is too stressed.

The objective of co-located competitive and collaborative leisure games is to encourage social interactions between players [9]. Collaboration is defined as the behaviour shown when multiple people work together towards a shared goal [10]. Collaborative and competitive games have been studied, often separately, looking at the affective states and behaviours they evoke. Different groups of researchers have investigated whether competitive games promote negative affective states but results are controversial. Some studies affirm they promote aggressive behaviour [11] while others argue that these games can also promote positive affect (if the player's motivation is winning, s/he might experience stress as positive affect) [12]. Kivikangas et al. [10] explored gender differences in emotional responses in collaborative and competitive games. The results revealed that males experienced more positive emotions during competitive than collaborative games whereas female participants evidenced no discernible difference.

Table 1. A summary of studies in affective gaming for solo and multiplayer games

Ref.	Play mode	Sensors	Self-rep. labels	Behaviours	Measured labels
[9]	Solo & Comp.	ECG, GSR, EMG & Resp.	Boredom, Engag. & Fun	N/A	Arousal
[10]	Collab. & Comp.	ECG, GSR, EMG	SAM & SPGQ	N/A	Valence & Arousal
[3]	Solo	ECG, GSR, EMG & Resp.	SAM		Valence & Arousal
[7]	Comp.	GSR	N/A	N/A	Arousal
[8]	Collab.	ECG	N/A	N/A	Arousal
[13]	Collab. & Comp.	ECG, GSR, EMG & Resp.	GEQ	N/A	Social interaction & Presence
Ours	Solo, Comp. & Collab.	ECG, GSR	GEQ & IQ	Non-verbal	Arousal

Notes: SAM: Self-Assessment Manikins. SPGQ: Social Presence in Gaming Questionnaire. GEQ: Gaming Engagement Questionnaire. IQ: Immersion Questionnaire

Collaborative games have been shown to lead to engagement, social interaction and positive emotions (i.e., enjoyment [9]). Mandryk and Inkpen [9] investigated the physiological changes in competitive and solo games (see Table 1). The study showed a significant increase in the sweating level (GSR) during the competitive mode, which correlated with a higher level of fun [9]. These results were confirmed correlating the physiological signals with the self-reported data gathered. However, this experiment did not look into differences between competitive and collaborative play modes. Chanel et al. measured the physiological compliance, defined as *the correlation between the physiological signals of a dyad* [13], in competitive and collaborative games both in co-location and remotely. They concluded that physiological compliance is higher in competitive games, with minor differences related to the location. In this paper we present a study where we measured the affective, physiological and behavioural indicators in solo, competitive and collaborative gaming in order to understand how players feel in these play modes and the differences in behaviour they exhibit in each mode.

3 The Study

Participants played a video game for Nintendo's Wii[1] console called *Boom Blox: Bash Party* (Fig. 1), a physics-based puzzle video game designed by Steven

[1] Nintendo's Wii console: http://www.wii.com/.

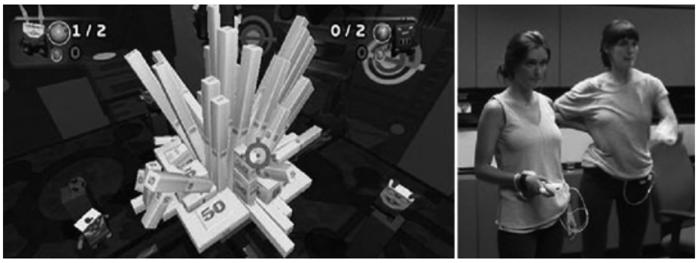

Fig. 1. Screenshot of Nintendo's Wii game *"Boom Blox: Bash Party"*

Spielberg. The game consists of knocking down a structure made of blocks by throwing balls against it using the Wii Remote controller as if it were the ball itself. Each block has a number drawn on it that indicates how many points it gives. We had to slightly modify the collaborative play mode in order to allow both players to play simultaneously without time limit. No prior experience was required to participate in this study, except both players within a pair had to know each other before the experiment to increase the chances of collaboration between them [14].

3.1 Tasks and Measurements

The players had to play *Boom Blox: Bash Party* in three play modes. In *solo*, players play alone and get points by knocking down the structure. In *competitive*, two players compete to get as many points as possible knocking down the blocks. In *collaborative*, two players play together to break the structure with as few throws as possible. The number of throws were counted for both players, so they had to talk and think about how to do it in the most efficient way. The duration of each play mode lasted 4–7 mins and the play order was randomised for every pair to avoid bias.

Subjective (self-reported) and objective (continuous and physiological) data was recorded from all players in every play mode. Table 2 summarises the data gathered and the features extracted. An electrocardiogram (ECG) to measure the heart's electrical activity was used, sampled at a rate of 512 Hz. We extracted the Heart Rate (HR), Inter-Beat Interval (IBI) and Heart Rate Variability (HRV). We also used a Galvanic Skin Response (GSR), which measures the activity of the sweating glands. The electrodermal activity is associated with stress and anxiety, an indicator of emotional arousal [5]. This sensor was placed in the hand holding the game controller and sampled at 51 Hz. The GSR sensor used also had an accelerometer incorporated to record the movements of the hand holding the controller. Baseline activity levels were recorded for all physiological signals to normalise individual differences.

Three questionnaires were designed using 5-point Likert scales: pre-experiment (PRE), post-play (PPQ) and post-experiment (POST) questionnaire. PPQ were given after each play with questions about player engagement [15] and immersion [16]. Questions were randomised to avoid any bias due to

Table 2. Objective (continuous) and subjective (self-reported) data recorded.

Measure	Sensor/method	Features	Type of data
ECG	Shimmer ECG sensor	Heart Rate (HR): mean & SD Inter-Beat Interval (IBI): mean Heart Rate Variability (HRV): Root Mean Square of Successive Differences (RMSSD)	Quantitative
GSR	Shimmer GSR sensor	Skin Conductance Level (SCL): mean & SD Skin Conductance Response (SCR): mean & SD	Quantitative
Motion	Accelerometer	Number of throws (peaks), quantity of motion, highest peak (velocity throw)	Quantitative
Video	Front-facing camera	Gestures, body position, spatial behaviour, number of gazes, positive and negative facial expressions...	Quantitative and qualitative
Self-report	PRE, PPQ & POST	Engagement, immersion, frustration, stress, enjoyment, effort, boredom	Quantitative

repetition of the questionnaire after each play mode. Finally, a video camera placed at one side of the monitor displaying the game recorded the experiment for observational analysis and qualitative data extraction.

3.2 Data Pre-processing and Feature Extraction

As all the physiological data was recorded using the same software, all the data was recorded at the same sampling rate. Data from all sensors was plotted to check if it was correct. The GSR data was extremely noisy since it was placed in the hand holding the controller, which was constantly moving and shaking while playing. We applied different filters such as lowpass or moving average filter to remove the noise, making the data considerably smoother although it was still too noisy to use in this analysis. ECGTools[2] was used to analyse the ECG and extract the R-peaks, which corresponds to individual heart beats. We then calculated the HR and IBI values per second and extracted the (HRV), which measures the variation of the frequency of heart beats over time.

The mean Quantity of Motion (QoM) of the Wii controller was computed from the accelerometer data. Using a peak detection algorithm, we extracted the number of throws of each player per play mode. Video recordings were manually annotated to determine the predominant facial expressions in each play mode as well as the non-verbal behaviours such as gestures, body positions and spatial behaviours (i.e.: moving around the room).

4 Analysis

4.1 Analysis Between Play Modes

Eight players (four pairs) took part in the experiment with a mean age of 30.88 (SD: 4.28). Half of the players preferred playing video games alone, three

[2] http://www.ecgtools.org/.

Table 3. Paired T-tests among play modes

Param.	Mean	SD	t(df)	Sig.
Mean HR	10.67	5.25	5.38 (6)	.002
Num. throws	20.75	7.50	9.03 (7)	.000
Mean QoM	1.07	.56	5.35 (7)	.001
Fastest throw	.50	.78	1.83 (7)	.109

Note: SD = Standard Deviation. df = degrees of freedom.

Table 4. HR correlations.

	Pair 1	Pair 2	Pair 3	Pair 4
Comp.	.509**	.165**	−0.066*	.200**
Collab.	.021	.034	.061	.022

Note: Significance of Spearman's rho: *$p < .05$; **$p < .01$.

collaboratively and only one competitively. Four out of the eight players reported in the POST questionnaire to have enjoyed the collaborative mode the most, three preferred playing competitively and one the solo mode. Players reported to be equally engaged with their colleagues during the collaborative (M: 3.88, SD: 0.99) and the competitive play mode (M: 3.25, SD: 1.16). No significant differences were found in the immersion level.

In order to analyse whether there was significant differences among play modes in the continuous features, we carried out various paired t-tests, specially between the competitive and collaborative play modes (Table 3). One of the players who reported neither enjoyment nor engagement in any of the play modes and whose physiological signals did not vary much across play modes, was removed in the HR paired t-test, which would just mean as if he would not have taken part on the experiment. The mean HR and the mean IBI showed very significant ($p < 0.01$) statistical difference between the competitive and collaborative modes, with a mean variation of 10.67 in the HR (SD: 4.09) and −100.24 in the IBI (SD: 63.35). Participants experienced a higher HR of 10 Beats Per Minute (BPM) average in the competitive play mode.

The accelerometer showed some significant ($p < 0.01$) differences, particularly in the number of throws and the mean QoM. The statistical difference of number of throws had a mean of 20.85 (SD: 7.01), meaning that players made on average 20 throws more in the competitive than in the collaborative play mode. This high difference is caused not only by the nature of the collaborative mode where players had to make as few throws as possible, but also due to the turn-taking strategy all pairs followed when playing together. The mean QoM of the hand holding the controller was higher in the competitive mode (see Table 3).

4.2 Physiological Analysis Within Pairs

In this section we compare the behavioural and physiological responses between the players within each pair, investigating the correlations in the continuous signals of the two players. Due to the intrinsic auto-correlation of the ECG signal, it is not possible to perform a simple cross-correlation with this data as it is biased [17]. One way to overcome this problem is to make a 1 s interpolation of the HR values in order to have an evenly spaced continuous data. Then a

Table 5. Spearman's correlations between continuous and self-reported data

Param.	Depend. var.	Rho	Sig.
Mean QoM	Norm. Mean HR	.413	.052
Mean QoM	Norm. Mean IBI	−.462	.053
Effort	Norm. Mean HR	.584	.001
Engage w/Partner	Norm. Mean HRV	−.535	.001
Enjoy w/Partner	Norm. Mean HRV	.265	.211
Enjoy w/Partner	Norm. Mean HR	.122	.571
Flow	Norm. Mean HR	−.157	.497

Table 6. Spearman's correlations between play modes at individual level

Play mode	Param.	Depend. var.	Rho	Sig.
Competitive	Effort	Engagement	.756	.030
	Effort	Immersion	.571	.139
	HRV	Fun w/partner	.639	.088
Collaborative	Effort	Engagement	−.103	.808
	Effort	Immersion	.130	.759
	HRV	Fun w/partner	.041	.923
	Mean Norm. HR Solo	Mean Norm. HR Collab	.929	.001

non-overlapping window of 3 s was generated for every single participant and play mode. Once the data was windowed, we were able to perform a normal Spearman's correlation between members of a pair in each play mode separately.

As shown in Table 4, all players experience a statistically significant higher correlation in HR when playing competitively than collaboratively. We think that the higher correlation of pair 1 during competitive mode might be due to their increased motivation levels as player 2 of this pair was the only one reporting to prefer playing competitively. This important detail might explain an emotional contagion between players. However, the low (and in some cases) negative correlation in the collaborative play mode can be again explained by the turn-taking strategy followed by all the pairs. In the collaborative mode, whilst one player experienced arousal while playing, the other player was more relaxed. For example, pair 3 in competitive mode have a very small negative HR correlation due to the lack of engagement, immersion and even enjoyment of the second player reported in the POST questionnaire. Therefore, player 1 was more activated than player 2 as their HR differ considerably.

4.3 Analysis Across Play Modes and Pairs

This analysis focused on the relation between continuous and self-reported data of all players. Prior to this analysis, we had to normalise the physiological data of each player to mitigate individual differences. Each player's ECG data was normalised according to his/her own baseline. In order to normalise the physiological data of each play mode, we divided the mean of the baseline by the mean of each mode, getting the percentage of increase for a particular play mode. For example, if the mean resting HR of one player was 73 BPM and the mean HR for this same person was 96 BPM in the competitive play mode, we can say that the HR increased by 131 % in that particular mode.

Once all the physiological data was normalised, it was correlated with objective (QoM) and subjective measures such as effort or enjoyment (Table 5). The mean QoM had a moderate positive correlation with the normalised HR (r .413, $p < .05$) and, at the same level, was negatively correlated with the IBI (r −.462, $p < .05$). This correlation between QoM and HR is probably related to the significant correlation (r .584, $p < .01$) of the mean HR with the effort reported in the questionnaires. These correlations are meaningful, since the BPMs increased with the required movement and effort needed to achieve a good performance.

The normalised mean RMSSD (Root Mean Square of Successive Differences) of the HRV showed a strong significant but negative correlation with engagement with the partner (r $-.535$, $p < .01$). This correlation demonstrates that the HRV is lower when the player is more engaged. Previous studies have demonstrated that HRV decreases with mental effort [9], meaning that when the subject is more focused, the body tends to be more relaxed and the heart activity settles down without much fluctuations.

4.4 Individual Analysis Between Play Modes

Since we are interested in how players experience each play mode at both a physiological level and through self-reports, we looked at each individual's data in the different play modes (Table 6). We examined the Spearman's correlations of effort with engagement and immersion. The rho coefficient in the competitive mode is clearly higher, which means that a higher effort leads to higher level of immersion and engagement.

The normalised mean HR in the solo and collaborative modes were also correlated, looking for relations in the physiological responses in these play modes. This analysis evidenced an extremely significant and very strong correlation (r .929, $p < .01$). Thereby, we can affirm that when a player is relaxed playing alone, s(he) will calm down at the same level when playing collaboratively.

4.5 Behavioural Analysis

The analysis in this section focuses on the video observations of the facial expressions, gestures, body positions and spatial behaviour of players. We manually labelled the facial expressions into 3 groups: positive (smiling or laughing), negative (frustrated or angry) or neutral. We also described spatial behaviour or movement as the activity of one individual moving through the surrounding environment (the room).

We divided each recorded video into three equal parts and annotated the predominant facial expressions for each part. The most common expressions in the competitive mode were negative as the players tried to win but not always got the expected results (getting stressed and even angry). Positive facial expressions were also present in this play mode, usually appearing at the end of the game when both players got more relaxed and talked about their performance. Some participants had recurrent 'specific' expressions such as biting their lower lip, sticking out the tongue or frowning, which displayed their frustration or engagement. The collaborative play mode elicited more positive facial expressions and laughters, and neutral faces were the most frequent in the solo mode.

When labelling body positions, gestures and spatial behaviour of players, we looked at their reactions and behaviours over the whole play mode. Overall, players had a more relaxed behaviour and body posture during the collaborative and solo play modes than when competing (Fig. 2), displaying a greater spatial

Fig. 2. Participants playing competitive (left) and collaboratively (right).

movement and more gestures such as head nods or moving arms around their body. Players changed their body position more often in this play mode, normally after each throw, and had more social interactions, conversations and mutual glances. In the competitive play mode, players were more static, barely moving their body or legs, and rarely speaking to each other until the game was over.

5 Results and Conclusions

In this paper we looked at the physiological signals and non-verbal behaviour indicators in solo, competitive and collaborative play modes for co-located gaming. The significant correlation of HR between players during the competitive mode, plus the significant mean HR difference compared to the other two modes, demonstrate a clear arousal increase when playing competitively. The strong correlation of the normalised mean HR in the solo and collaborative modes show that the arousal level in these modes are related. HRV is also an interesting cardiac feature to measure engagement [3], evidenced by a significant negative correlation with the self-reported engagement with partner. Video observations also revealed that competition evoked a tense behaviour in players, whereas playing collaboratively players were more relaxed and positive (Fig. 2).

However, HR must be interpreted carefully in gaming. While an increase in HR, caused by the cardiac sympathetic activity, is associated with affective arousal, a slow HR inflicted by the cardiac parasympathetic activity is related to attentional engagement [18]. Since video games can evoke both states simultaneously, HR alone might not be a good measure of arousal in games. Although skin conductance is a good and unambiguous indicator of arousal [2], it is very prone to noise. For this reason, GSR is not appropriate for experiments where the players have to constantly move their hands.

The results presented from this study are indicative of the affective states and behaviours players manifest in different play modes. Further research will investigate how affective states can be measured using non-invasive sensors and how this data can be used to enhance user experience in competitive and collaborative gaming. Also, it would be interesting to look at how certain game events have an impact on the player's affective states in the three play modes.

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