Correlating Facial Expressions and Subjective Player Experiences in Competitive Hearthstone

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ABSTRACT

In this study, we used recordings of players' facial expressions that are captured during competitive Hearthstone games to analyse the correlation between in-game player affective responses and subjective post-game self-reports. With this, we aimed to examine whether eye gaze, head pose and emotions gathered as objective data from face recordings would be associated with subjective experiences of players which were collected in the form of a post-game survey. Data was collected during a live offline Hearthstone competition, which involved a total of 17 players and 31 matches played. Correlation analyses between in-game and post-game variables show that players' facial expressions and eye gaze measurements are associated with both players' attention to the opponent and their mood influenced by the opponent. In future research, these results may be used to implement predictive player models.

CCS CONCEPTS

• **Human-centered computing → HCI theory, concepts and models**.

KEYWORDS

Facial expression analysis, competitive games, hearthstone, player experience, player affect, game experience questionnaire

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1 INTRODUCTION

Competitive video gaming, also known as Esports, is a field of constantly growing industrial and scientific interest. In recent years, scientific research has revolved around various aspects of Esports, from comparing them to traditional sports [16] to implementing multi-agent systems able to beat the world champion team of Dota 2 [4]. Regarding player affect in particular, studies have discussed player motivation [14], psychology [3], and physiology [5, 21].

This study presents an approach towards player affect analysis through facial expressions, during competitive games of Hearthstone. Hearthstone is one of the most popular one-versus-one digital Collectible Card Games, played as an Esport since 2014. Much like poker, Hearthstone is played in a partially observable environment, where players can see their own cards and the cards on the table but have little information on their opponent's hand. Even though Hearthstone is mostly played online, disabling physical interactions between players, most major Hearthstone competitions are held offline with all players physically present in a venue. In this context, analysing a player's facial expressions may yield information not only on their overall affective state, but also on their in-game strategy, given the current state of the game board. However, when a player's facial expressions are analysed, to be able to better make sense of the data, there is a need to know what these expressions correspond to in terms of subjective player experiences. This purpose motivated us to investigate how we can examine eye gazes, head poses and emotions gathered from facial expressions in terms of players' subjective experiences. Our goal was to uncover whether these objective measures are related to and translated into players' perceptions of their involvement levels, moods and their relationships with their opponent. Ultimately, our aim is to use this dataset to implement predictive models of player affect based on facial expression analysis.

We ran a live offline Hearthstone competition, where 17 players competed for the top three prized spots. During the matches, we recorded each player's face along with that player's perspective of the game board. In addition, we employed the Game Experience Questionnaire (GEQ) [15] to retrieve post-game subjective measurements of players' experiences. In the present paper, we present the preliminary results of a correlation analysis between players' facial expression metrics and their subjective reports.

2 RELATED WORK

Human-Computer Interaction (HCI) and affective computing [23] in particular, are fields of increasing popularity in video game research. Modern sensor technology enables the unobtrusive extraction and analysis of player affective responses, which can be used for player modelling [29], implementation of adaptive games [6] and procedural content generation [30]. Facial expression analysis

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Figure 1: Snapshot of a game in the 2016 Hearthstone world championship[20]. Players are seated facing each other, allowing eye contact.

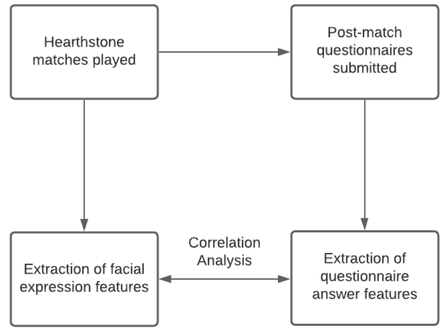

Figure 2: Overview of the methods employed in the present paper.

is a non-invasive affective input channel, as it can be achieved with inexpensive commercial hardware and open-source software such as OpenFace [2]. Facial expression analysis and video games have been combined in multiple studies discussing various topics, such as affective gaming [22, 27], game personalisation [7], player affect evaluation [24, 28] and alternative gameplay mechanisms [25]. Recently, Doyran et al. [9] published a rich dataset that enables multi-modal, multi-player affect and interaction analysis through capturing the facial expressions of board game players.

When card games are concerned, digital or tangible, players often seek to extract hidden information from their opponents by analysing social signals such as speech, body motion and facial expressions [17]. Slepian et al. [26] discuss that poker players' motor actions oftentimes betray their intentions, possibly emitting unintended signals to opponent players about their hand quality. The same principle can apply to a digital card game like Heartstone; offline Hearthstone competitions often allow eye contact between players, despite it being a digital game (see Figure 1). By analysing player facial expressions during competitive Hearthstone games, we may not only assess their affective state, but also extract information on their in-game strategy. Although the latter is outside the scope of this paper, it is one of the future goals of this work in progress.

Affective computing techniques have been directly applied to Esports, mainly for player affective state monitoring. Wearable sensors have been employed to collect affective data from professional Counter-Strike players [19] and semi-professional League of Legends players [5]. In this study, we look for correlations between player social signals (through facial expressions) and subjective reports of affect. To our knowledge, only a limited number of studies discuss player facial expressions during multi-player, competitive video games [1, 10].

3 METHOD AND DATA COLLECTION

A total of 17 players formed a tournament bracket, resulting in 31 matches played. One match was excluded from the dataset because of webcam recording failure. In total, 156 game recordings were collected. Applicants were all male, with an average age of 22.7 years (sd = 3.6). Before their first match, all participating players signed an informed consent form agreeing to the recording of their facial reactions throughout the game competition.

The competition was held in Tilburg University's Game Lab. In the lab, five pairs of high-end gaming desktop computers were placed in two rows facing each other. For every match, the opposing players were positioned in one of the computer pairs. To enable eye contact between opponents, the computer's monitors were set to minimum height. Webcams were mounted on top of each monitor, recording participants' faces during the matches.

To strengthen the competitive nature of the tournament, prizes were added for the players who finished in the top three positions. Prizes included peripheral gaming hardware and digital gift cards. We believe that through tangible prizes, players' motivation to win is increased, resulting in a stronger sense of satisfaction when victorious, and a stronger sense of disappointment or frustration when losing. We expect these affective responses to be expressed both through players' facial expressions during the games and through their subjective post-match reports. An overview of the data collection and data analysis methods used in this paper is provided in Figure 2.

Regarding facial expression analysis, webcam recordings were processed through the OpenFace [2] facial expression analysis toolkit. OpenFace provides per-frame estimations of presence and intensity for several facial Action Units (AU), as described in the Facial Action Coding System (FACS) [13]. In particular, OpenFace can detect AUs 1, 2, 4, 5, 6, 7, 9, 10, 12, 14, 15, 17, 20, 23, 25, 26, 28, and 45. To maximise the robustness of our collected dataset, we discarded all video frames where OpenFace's confidence of AU estimation was below 98%. AU intensity estimations were translated into one of the six basic emotions [12] (happines, surprise, fear, sadness, disgust and anger) intensity estimations following Du et al. [11]. We calculated an average value of intensity for each facial expression of emotion, per player, per match played. Lastly, we calculated the root-mean square error of successive differences (RMSSD) for head pose and eye gaze measurements, per player, per game. The latter features serve as a descriptor of overall player head and eye movement during gameplay.

Regarding the post-match questionnaires, we employed GEQ's in-game and social presence modules. After each match participants

Table 1: List of variables extracted from post-match questionnaires and facial expression analysis data.

Post-match report (GEQ)	
Match score	Luck defined outcome
Negative affect	Positive affect
Competence	Flow
Tension	Challenge
Behavioural involvement	Psychological involvement
Influenced opponent's mood	Influenced by opponent's mood
Attracted opponent's attention	Paid attention to opponent
Facial Expression Analysis (OpenFace)	
RMSSD eye gaze	RMSSD head pose
Average intensity happy	Average intensity angry
Average intensity sad	Average intensity disgusted
Average intensity fearful	Average intensity surprised

submitted self reports, scoring their in-game positive/negative affect, competence, challenge, flow, tension, behavioural and psychological involvement. Additionally, a Hearthstone-related question was added to the questionnaire: "To what extent does the player feel that luck defined the outcome of the match?" Since "luck" (the game's built-in randomness) can be a determining factor in Hearthstone, we expect perceived luck to be associated to increased levels of player frustration or satisfaction. Lastly, before participating in the tournament, players signed an informed consent form, along with a report on their subjective prior experience level in Hearthstone (1 – *not at all* to 5 – *extremely experienced*), and a report on weekly amount of hours spent on Hearthstone. The list of variables extracted is presented in Table 1.

4 RESULTS

We ran zero-order correlation tests for each variable extracted through facial expression analysis and post-game reporting. Each GEQ related variable is derived from combined questionnaire items according to Ijsselsteijn et al. [15]. To emphasise focus on interactions between opponents, we also ran correlation analyses on four specific GEQ items, namely "Influenced (by) opponent's mood" and "Attracted opponent's attention/Paid attention to opponent". These four items also participate in the calculation of psychological & behavioural involvement variables. Statistically significant correlations found are listed in Table 2. Our aim was to explore correlations between subjective player self-reports and objective facial expression measurements; for that reason, we chose to focus on inter-modality correlations.

In Table 2 we observe several moderate inter-modal correlations. More specifically, player eye gaze seems to have a positive correlation to players' psychological involvement, which includes their perception of influence on the opponent's mood. Similarly, head pose shows moderate correlation to psychological involvement, influencing and paying attention to the opponent. No correlation was found between player facial expression analysis variables and the "luck" variable. As far as facial expressions of emotion estimations are concerned, higher happiness scores are moderately correlated to psychological and behavioral involvement, increased attention between both opponents and high influence on each other's mood. Similarly, higher estimations of fearful facial expressions are moderately correlated to psychological involvement, mostly deriving from players being influenced by their opponents. Lastly, we observe that high scores of anger have a mild positive correlation to influence on the opponent's mood.

Table 2: Results of zero-order correlation tests. Only statistically significant correlations are listed. Correlation coefficient provided in parentheses, single asterisk (*) indicates $p <= 0.05$ and double asterisk (**) and bold indicates $p < 0.01$.

Tested variable	Significantly correlated variables
RMSSD eye gaze	**Psychological involvement** $(.33^{**})$ **Influenced opponent mood** $(.34^{**})$
RMSSD head pose	Psychological involvement $(.31^{*})$ Influenced opponent mood $(.32^{*})$ Paid attention to opponent $(.29^{*})$
Average intensity happy	**Psychological involvement** $(.40^{**})$ **Behavioural involvement** $(.42^{**})$ Challenge $(-.30^{*})$ **Paid attention to opponent** $(.45^{**})$ Attracted opponent's attention $(.27^{*})$ Influenced opponent's mood $(.27^{*})$ **Influenced by opponent's mood** $(.44^{**})$
Average intensity fearful	**Psychological involvement** $(.40^{**})$ Behavioural involvement $(.32^{*})$ **Challenge** $(-.35^{**})$ Negative affect $(.30^{*})$ **Influenced by opponent's mood** $(.52^{**})$ Paid attention to opponent $(.32^{*})$
Average intensity angry	Influenced by opponent's mood $(.28^{*})$
Average intensity surprised	Challenge $(-.26^{*})$
Average intensity disgusted	Tension $(.28^{*})$ **Negative affect** $(.33^{**})$

5 DISCUSSION

The correlation analysis exposed some interesting findings. First and foremost, a moderate correlation between players' eye gaze and influence on opponent mood seems to support that players had eye contact during the games. Although this correlation yields little information as to how the opponents' mood was affected, or whether eye contact was frequent, intimidating or just observatory, this is a result worthy of further investigation. We believe that annotations of eye contact between players, along with in-game metrics such as player hand quality, in-game aggression/risk taking and overall playstyle, may grant us further insight into this relationship. Ultimately, our aim is to be able to model the opponent's playstyle by analysing their facial expressions.

Furthermore, we observe how certain facial expressions of emotion seem to be significantly correlated to paying attention to and receiving attention from the opponent. In particular, an increase in happiness shows positive correlation to paying attention to the opponent, while opponent influence seems to be correlated to both happy, fearful and angry facial expressions. We suspect that interaction between opponents may cause a "transfer" of emotion from one player to another. Meaning that in a one versus one context, an in-game event that brings happiness to one player, might make their opponent feel angry or frustrated. Although calculating an average estimation of emotion over the entire course of a match means a lot of information is lost, we believe that interactions between players definitely have an impact on their mood. Being able to recognise the opponents internal affective state, may be a rich source of in-game information that players do not have direct access to.

Overall, the main unique contribution of this study is that it shows that we expect that players' subjective experiences can be derived from conducting eye gaze and facial expression analyses. Present study also hints that eye gazes and emotions may have an influence on the opponent's subjective experiences. However, dyadic analyses would be needed in order to more definitively state that players can directly affect their opponents with their gazes and facial expressions.

As future work, we believe that two investigations are necessary. First, in-game data should be analysed to enable the implementation of player models with respect to their in-game playstyle. Without any information about the actual gameplay (apart from the final score), few conclusions can be reached regarding the relationship between player affective state, opponent interaction and playstyle. Second, more in-depth facial expression analysis is currently being conducted. We believe that defining and extracting a wide list of spatio-temporal facial expression features is crucial to the continuation of this study. One example may be the detection and analysis of facial micro-movements [8] during gameplay. Such signals enable a more fine-grained study of player affect, associated with opponent interactions and in-game events. Lastly, we acknowledge that the male dominance in our dataset may harm the generalisability of the obtained results. However, it has been indicated that males comprise the vast majority of Esports players [18].

6 CONCLUSION

In this paper, we present a work in progress regarding player facial expression analysis during competitive Hearthstone games. We have collected a dataset, consisting of 17 players who participated in a total of 31 matches during an offline live Hearthstone competition. During gameplay, we extracted and analysed affective signals from facial recordings, while we employed the GEQ to extract post-match subjective scores of experience. The present study focuses not only on correlation between in-game and post-game player affect, but also touches upon the relationship between facial expressions and interactions between opponent players. Results show that there is a moderate correlation between player eye gaze measurements and opponent influence and attention, while moderate correlation was also found between the latter and facial expressions of happiness and fear. These findings lead us to the conclusion that, in the context of card games, eye contact between opponents is a social signal that not only carries affective information from one player to another, but may also identify players' in-game intentions. In addition, it was shown that the cumulative facial expression calculations can give out information about the overall subjective experiences of players. Our future studies aim towards player modelling, mainly through facial expression analysis and in-game data.

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