Towards Multi-modal Stress Response Modelling in Competitive League of Legends

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***Abstract*—With the constant rise in popularity of competitive video gaming (also known as Esports), Esports analytics has been a field of growing scientific interest in the recent years. Studies discussing player behaviour, skill learning and team performance have been conducted through Multiplayer Online Battle Arena games such as League of Legends. In this paper, we propose a multi-modal approach towards stress response modeling in competitive LoL games. We collect wearable physiological sensor data, mouse & keyboard logs and in-game data in order to study the relationship between player stress responses and in-game behaviour. We discuss the design criteria and propose future studies using the collected dataset.**

***Index Terms*—Esports, Competitive video games, League of Legends, Player modelling, Multi-modal, Player stress response, Player physiology**

I. Introduction

League of Legends (LoL) has become a leading Esports title, amassing over 100 million monthly active users in 2016 [1] and over 6 million U.S. dollars as prize money for the 2018 LoL World Championship [2]. However, MOBA games remain largely unexplored with respect to player behaviour modelling [3].

In recent studies where player behaviour is analysed through Online Battle Arena (MOBA) games, researchers make a clear distinction between in-game and out-of-game player skills, where in-game skills refer to mechanical expertise such as avatar and game interface control [4], and out-of-game skills derive from cognitive aspects such as cooperation [5], tacit communication [6] and player experience [7].

In this study we build a multi-modal dataset, through which we enable the exploration of relationships between in-game and out-of game elements of player behaviour. More specifically, during competitive LoL games, we use mouse and keyboard tracking as well as in-game statistics to monitor players' in-game performance, while we measure player stress responses through wearable physiological sensors. Ultimately, we aim to facilitate the study of correlation between player stress level and in-game performance.

II. Related Work

We have found a relatively low amount of relevant studies in the field of player stress response modelling during competitive gaming. Below, we present studies on both serious and competitive games which discuss players' cognitive performance, including monitoring of players' stress responses.

A. Multi-modal stress response modelling

When analysing humans' stress responses, multi-modality has been indicated as the preferred approach [8], [9]. Carneiro et. al. developed a system for non-invasive multi-modal stress detection, using an arithmetic task mobile game. Players were asked to make mathematical calculations under heavy time pressure. Results show a strong correlation between the amount of experienced stress and players' interaction patterns with the mobile device. In our study, we hypothesise that heightened player stress levels may correlate to players' in-game performance, as measured through in-game statistics and mouse & keyboard usage patterns. To that end, we choose to build a multi-modal dataset through which this hypothesis can be adressed. In this paper, we use the term 'player stress' to refer to game-induced player arousal, which can derive from both positive (e.g. excitement) and negative (e.g. sadness) affective states.

B. Cognitive performance of MOBA players

MOBA game related studies have shown that there is a strong correlation between players' cognitive and in-game performance [10]–[12]. More specifically, Bonny et. al. [12] examined the correlation between cognitive and in-game player skills, revealing that players with higher levels of MOBA gaming expertise respond faster to decisions that rely on spatial memory. They suggest game research to be conducted in gaming tournaments, where researchers can gain access to gaming experts. Based on the latter, we have chosen to build our dataset within an official LoL competition, where all participants (players) of a team are physically present in the same location.

Similarly, Pereira et. al. have conducted a study within the largest official LoL competition in Brazil (known as CBLoL). They define a daily routine involving physical and mental excercise, and explore whether such a routine can increase cognitive performance. Through a heart rate monitoring belt and evaluation questionnaires, they illustrate that players who followed the suggested routine have shown improvement in selective attention, memory, visuospatial and math abilities, while they reported lower levels of anxiety during competition. In our study, we monitor player physiological responses through wearable sensors, through which we aim to explore whether (a) increased player stress levels have an effect on in-game performance and (b) whether certain in-game elements cause significant fluctuations on player physiology.

For an in-depth literature review on MOBA game research, we refer readers to Mora et. al. [3].

III. Design Criteria

Numerous studies around MOBA games employ large-scale datasets including thousands of games and players. However, in order to enable research on player stress responses, we choose to build a (relatively limited) dataset which satisfies the following criteria:

1) *Tacit reaction monitoring*
According to Kim et. al. [6], similarly to real world organisations, MOBA games require competitiveness and fast decision making from the players. Under such circumstances, tacit coordination plays a large role in team environments. We consider physiological stress responses to be tacit reactions which players should recognise and control during competitive games. We believe that player emotions, and specifically increased stress levels, are likely to not be expressed verbally within a team. However, we hypothesise that such emotional reactions have a significant effect on players' in-game performance.
2) *Physical presence*
In order to be able to monitor player stress responses, we require the physical presence of players in a laboratory area. This way, we enable collection of data from wearable physiological sensors, as well as tracking of player interactions with the computers' input devices (mouse and keyboard).
3) *Competition*
All games included in our dataset are played within an official Esports competition. The competitive nature of these games is bound to increase player stress levels, since victory becomes the players' main motivation.

We expect the study of player stress responses through mutliple modalities to yield promising results; to our knowledge, this particular field within Esports analytics remains unexplored thus far.

IV. Data Collection

We have collected a dataset in collaboration with the Tilburg Student Esports Association (TSEA) Link[1]. Link's LoL team "Rupees" participated in the 2018-2019 Dutch

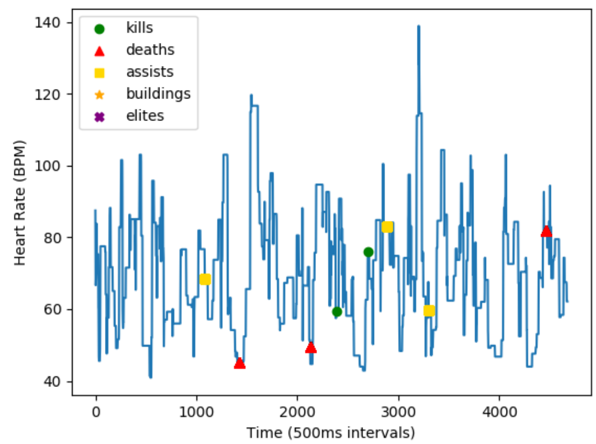

Fig. 1. Plot of a player's (id: 'lol-3') heart rate (beats per minute) during a competitive LoL game (game id: 3935361323), with annotations of in-game events (player kills, deaths, assists, building kills and elite monster kills).

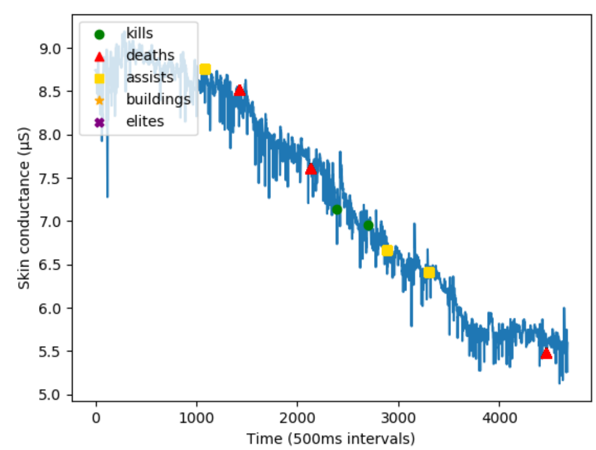

Fig. 2. Plot of a player's (id: 'lol-3') skin conductance (μS) during a competitive LoL game (game id: 3935361323), with annotations of in-game events (player kills, deaths, assists, building kills and elite monster kills).

College League's (DCL[2]) "Talent League". The team consists of eight players (7 male) of whom five form the starting lineup and three are substitutes. The average player age is 21.5 years with a standard deviation of 1.6 years. While seven out of eight players are native Dutch speakers, the team fluently communicates in the English language during games.

For the DCL's Talent League, a group of 11 teams participated in a single best-of-two round-robin pool. This means that for every round of the tournament (10 rounds in total), each team was assigned an opponent against whom they played two LoL games, switching sides in between games. Data was collected for 8 out of 10 rounds of the DCL. For each round, the Rupees gathered and played their match in Tilburg

[1]http://tsea.link

[2]http://www.dutchcollegeleague.nl/competition/tl

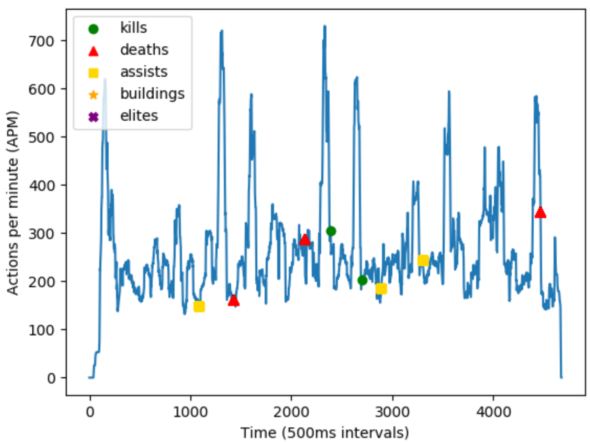

Fig. 3. Plot of a player's (id: 'lol-3') keyboard & mouse actions per minute (APM) during a competitive LoL game (game id: 3935361323), with annotations of in-game events (player kills, deaths, assists, building kills and elite monster kills).

University's Game Lab, using the laboratory's computers. Players who could not physically attend a session played from their home environment, and are excluded from the dataset. Data was collected using three input channels:

1) Keyboard & mouse logging
Recording User Input (RUI) [13] was running as a background process on each computer, recording player mouse and keyboard activity. RUI logs include every mouse click, mouse move and keyboard key pressed, accompanied by an absolute timestamp. We selected to record keyboard and mouse activity under the assumption that players' interactions with the computer's input devices may be descriptors of both player stress responses and in-game performance.
2) Wearable physiological sensors
For three out of eight sessions, Shimmer3 GSR+ [14] wearable sensors were attached to the player's mouse controlling hands. All players indicated that attaching the sensors to the mouse controlling hand felt more comfortable than the keyboard controlling hand. Shimmer3 GSR+ logs include measurements from a photoplethysmograph (PPG) for heart rate monitoring, a galvanic skin response (GSR) sensor to measure skin conductivity, as well as 3-axis accelerometer, gyroscope, and ambient temperature and atmospheric pressure measurements. Sampling rate is set at 20Hz, while every datapoint generated is accompanied by an absolute timestamp. We expect variation in player stress levels during gameplay to be detectable through the Shimmer3 GSR+ wearable sensors, mainly through skin conductance (SC) and heart rate (HR) measurements. These particular sensors have been employed in studies discussing the effect of stress on player analytical skill performance in applied games [15].

TABLE I
OVERVIEW OF THE COLLECTED DATASET. FOR EACH PARTICIPANT, THE TOTAL NUMBER OF GAMES PLAYED AND MEAN VALUES OF MOUSE & KEYBOARD APM, HEART RATE (HR) AND SKIN CONDUCTANCE (SC) ARE ILLUSTRATED. FOR PARTICIPANTS '$lol-6$' AND '$lol-7$', NO PHYSIOLOGICAL SENSOR DATA WAS COLLECTED.

Participant id	Total games played	Mean APM in-game	Mean HR in-game (BPM)	Mean SC in-game (μS)
lol-1	13	301.9	81.9	4.2
lol-2	14	259.0	74.4	3.1
lol-3	19	262.0	71.5	14.5
lol-4	21	314.3	77.9	9.0
lol-5	17	186.7	75.3	3.1
lol-6	6	225.4	–	–
lol-7	1	192.6	–	–
lol-8	8	188.2	78.0	2.0

3) In-game logs
In-game logs were collected through the Riot Games API[3]. They are separated into two files, one containing post-game statistics for each player and the other containing an extensive timeline of in-game events. All in-game events are accompanied by absolute timestamps. For a detailed preview of in-game data files, we refer readers to the Riot Games API documentation[4].

In total, eight sessions of data collection resulted in approximately 2.4 Gigabytes of files, including mouse/keyboard, physiological sensor and in-game activity tracking. We have made the dataset available at https://surfdrive.surf.nl/files/index.php/s/oVzG4gbAsef6eNm.

Visualisations of the collected data are illustrated in Figures 1 – 3. In these plots, we show physiological sensor and keyboard & mouse logging data of a single participant gathered during a competitive LoL game, with annotations of in-game events. An overview of the collected data is provided in Table I.

V. LIMITATIONS & FUTURE WORK

Our main scientific focus in the field of Esports analytics is multi-modal player stress response modelling. While we have been conducting research regarding player stress response modelling in the context of serious games [16], we consider competitive games to pose great challenges when analysing player behaviour.

We recognize that during a competitive game, player stress levels can be affected by a multitude of factors, including in-game events, player experience and/or skill level, or even social factors such as team communication and inter-player relationships. As a consequence, player stress response models implemented using physiological and in-game data may still fail to detect the sources of increased player stress levels. Furthermore, given that competitive MOBA games can be

[3]Riot Games is the company developing League of Legends.
[4]https://developer.riotgames.com/api-methods/

an intensive high-tempo task [6], we expect to confront high amounts of player-generated noise (such as movement artefacts) in the sensor data. For that reason, we consider the pre-processing of raw sensor signals and extraction of stress-related features a crucial part of any future study. For example, noise artefacts in the raw physiological sensor signals may be detected and filtered out through synchronisation with the mouse activity signal. In order to facilitate player stress response modeling, baseline measurements in resting and stress (non-game) conditions will be collected and added to the dataset.

Despite the above limitations, we consider player stress response modelling a feasible task given the collected dataset. Future studies will focus towards measuring the effect of player stress levels on their in-game performance, by implementing personalised player stress response models. By building accurate player stress response models, we can then detect the "optimal" levels of stress, where each player's in-game performance is maximised.

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